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A methodology for microstructure-based structural optimization of cast and injection moulded parts using knowledge-based design automation

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Abstract

The local material behaviour of cast metal and injection moulded parts is highly related to the geometrical design of the part as well as to a large number of process parameters. In order to use structural optimization methods to find the geometry that gives the best possible performance, both the geometry and the effect of the production process on the local material behaviour thus has to be considered.

In this work, a multidisciplinary methodology to consider local microstructure-based material behaviour in optimizations of the design of engineering structures is presented. By adopting a knowledge-based industrial product realisation perspective combined with a previously presented simulation strategy for microstructure-based material behaviour in Finite Element Analyses (FEA), the methodology integrates Computer Aided Design (CAD), casting and injection moulding simulations, FEA, design automation and a multi-objective optimization scheme into a novel structural optimization method for cast metal and injection moulded polymeric parts. The different concepts and modules in the methodology are described, their implementation into a prototype software is outlined, and the application and relevance of the methodology is discussed.

1 Introduction

As the demands for low weight, reduced emissions and reduced environmental impact increases in areas as e.g. transportation and outdoor power products as chainsaws, the request for optimization of engineering structures increases accordingly. This drives the importance of designers to increase the load-bearing efficiency of parts, and increases the request for Computer Aided Engineering (CAE) tools and methods, as shape and topology optimisation, to identify geometries that fulfils the specified objectives. However, in order to be truly optimal from a company and customer perspective, the part also need to simultaneously fulfil a multiple of other objectives, as high manufacturability and robustness, legislation demands, and ergonomic aspects as

low levels of noise and vibrations. To successfully meet all these objectives in a short development time, a close interaction and collaboration between many different areas of the industrial product realisation process is required [1].

Many materials exhibit an interdependence between manufacturing and material behaviour. Casting is a manufacturing process able to generate near net shape components, while producing complex geometries in small as well as large series in a cost efficient manner. This design freedom is further enhanced by new technologies as e.g. 3D printing of moulds [2], making casting a modern technology highly suitable for creating parts with complex geometries and high load-bearing efficiency. During the solidification of cast metals, local variations in e.g. geometry and solidification conditions causes local variations in microstructure, leading to local variations in material behaviour throughout the geometry. These variations have been found to being able to alter the distribution of stresses and strains in castings when the casting is subjected to load [3]. Geometrical changes alter this heterogeneous distribution of material behaviour, thus causing an interdependent relationship between geometry and material behaviour that needs to be considered in structural analyses methods for castings. To address this topic, a simulation strategy denoted *the closed chain of simulations for cast components* has previously been presented by one of the current authors [4]. The strategy uses casting process simulations to generate microstructure-based mechanical material behaviour, which is incorporated into Finite Element Analyses (FEA) of the casting.

In injection moulded polymeric parts, especially made in glass-fibre filled materials with highly anisotropic material properties dependent on the glass-fibre orientation [5], manufacturing parameters as ingate position etc. highly influences the distribution of variations in local material properties in a part as well as the position of local reductions in mechanical properties by e.g. weld lines [6].

It is thus of utmost importance that these effects of the manufacturing process on the local material performance is considered in geometrical optimization methods, or incorrect predictions will be made and incorrect conclusions will be drawn regarding the behaviour and performance of the part in operation.

Previous structural optimisation methods for cast parts typically uses simplistic geometrical demands for design rules [7] or draw direction [8], and does not consider process steps as mould filling and solidification or the relationship between microstructure and local mechanical properties. Other works consider homogeneous material behaviour for the elasto-plastic behaviour while specific material properties as ultimate tensile strength are heterogeneously scaled based on heat extraction related parameters as solidification time from casting process simulations [9]. The relevance of considering manufacturing aspects as draw direction to generate geometries suitable for casting in topology optimisation of cast parts has been reviewed [10], but the heterogeneous material behaviour of castings has not been addressed. No previous method for cast parts has been found where heterogeneous material behaviour is used, or casting process simulations fully integrated into the structure optimisation to generate and incorporate geometry-dependent microstructure-based elasto-plastic stress-strain behaviour into the optimisation routine.

For polymeric parts, integrated simulation methods to predict heterogeneous elastic material behaviour have been developed for semi-crystalline polymeric parts [11] and short fibre composites [12]. For glass-fibre reinforced materials, a method to identify process parameters (e.g. gate location) to obtain the predicted optimal fibre-orientation for given conditions has been proposed [13]. However, a structural optimization method for injection moulded polymers with full integration of heterogeneous anisotropic non-linear material behaviour based on predicted glass-fibre orientation has not been found in the literature.

In a traditional sequential product realisation process, where the development moves from designer to structural analysis to production as illustrated in Fig. 1a, the knowledge and information from the engineers within the different disciplines enters the product realisation chain at different subsequent steps of the process. The amount of knowledge that can be added in each step down the process decreases, since the time and possibilities to introduce changes to the product continuously decreases. This approach tends to lead to a lot of design iterations and loop-backs, since important changes to ensure structural integrity or enable manufacturability are discovered late, causing long lead times and high costs.

In the present work, a new method for microstructure-based structural optimization of castings is presented. *Microstructure-based* implies that in each iteration of the optimization loop microstructural features are predicted using a manufacturing process simulation and considered in the structural analysis. A knowledge-based engineering (KBE) perspective is adopted to identify the workflow in the optimization loop, see Fig. 1b. The concept of Knowledge Based Engineering (KBE) is further described and reviewed elsewhere [14], and has previously been applied on system levels e.g. aircraft design [15] and the automotive area [16]. The current methodology aims to promote and enable the focus on multidisciplinary product knowledge and collaboration at early stages of the product realisation process. A methodology which takes local material behaviour into consideration is relevant for engineers within engineering design, materials science, production and CAE, and will enable new insights into the interdependence between disciplines as design and manufacturing.

Fig. 1. Schematic product realisation approaches a) Traditional sequential process with loopbacks. b) The knowledge-based process used in the current approach.

2 Methodology

In the current framework, a parametrised CAD-model serve as the starting point (process step 1 in Fig. 2), where geometrical features, parameters and constraints are introduced to represents design intent and the geometrical limitations for the part. Topology optimization methods based on density-scaling within a black-box geometry are highly useful to generate initial design concepts to serve as a starting point for designers, but in the context of manufacturability they have clear limitations. Such a volume with density variations is not physically achievable, and the CAD-representation can't be directly used for further simulations or analyses without manual or numerical interpretation [17]. Using the parametric model, fully defined solid CAD-models are here rather updated than generated for each alternative design. The loop as presented in Fig. 2 is in other words preceded by the utilization of topology optimization to develop the parametrized CAD-model. These parameterized CAD-models can allow topology changes by suppressing or activating various geometrical features and hence allow for the evaluation of a set of topological suggestions. The benefit of utilizing CAD-models in this manner is that it enables direct integration of manufacturing process simulations into a structural optimization routine, and in addition the result after optimization is a solid CAD-model which can be directly used for detailing and subsequently serial production.

The suggested approach is implemented into a prototype software which is based on the automation of a set of engineering actives, as illustrated in Fig. 2 forming an optimization loop. The different engineering tasks includes *Update Geometric Model*, *Generate Mesh*, *Execute Manufacturing Simulation*, *Render FEM-model with Local Material Data*, *Execute Simulation*, *Analyse Output*. These tasks are controlled and executed using a design automation system based on knowledge-objects. The modules and the control system are described in detail in the following sections.

Fig. 2. Overview of the current approach. The interaction between different modules in the optimization routine are controlled using design automation, and knowledge objects are used to carry the information.

2.1 Automation using knowledge objects

To assist the implementation of knowledge into engineering software, object-oriented technology has been adopted into so called knowledge objects. Knowledge objects may consist of e.g. geometry parameters (wall thicknesses, distances, radii, angles, spatial limitations etc.), material parameters (material or alloy type, chemical composition etc.), performance objectives

(stresses and strains, vibrations etc.) or other types of knowledge and demands (legislation, cost, etc.).

Knowledge objects have previously been applied to automate the manufacturability analysis process for draw bending of circular tubes, to automatically setting up and executing non-linear FEA-simulations, while handling multiple types of extrusions and making the interpretation of the simulation results [18]. In the mentioned draw bending system the simulations were performed using CATIA™ for geometry modelling and meshing, and LS-DYNA™ to process the simulation. In 2014 a new system was developed combining SolidWorks™, ANSA™ and LS-DYNA™ to simulate car collisions focusing on keeping roof racks at top of the roof [19]. That system made the modelling of FEA-related features possible so that design engineers could execute the simulations while the FEA-specialist could focus on developing the simulation processes. In this paper a combination of these two systems, see Fig. 3, serves as the base to engineering automation through knowledge objects.

Fig. 3. Simplified class diagram showing the knowledge based system where knowledge objects are used as the knowledge carriers.

A **Knowledge Domain** (see Fig. 3) is a set of parameters and knowledge objects to which an inference engine is applied to process system inputs to outputs. A **Knowledge Object** contains a list of input parameters, a list of output parameters, and a method for processing input parameters to output parameters. Other fields may be added to knowledge objects such as *constraints*, *owner*, *categories*, *precision*, and *comments*. *Owner* is used to trace who is responsible for the knowledge object and its method (the task it performs). The field *categories* can be used to sort knowledge objects into groups. *Comments* are used to add information usable for explanation extractions and debugging facilities. Finally, the list of *constraints* and the *precision* values are used to add meta-knowledge (i.e. knowledge about when to apply the automated knowledge). When implementing the knowledge objects, they should be defined in a way that makes them autonomous. Since the methods used to process information preferably are external software applications, the applications should be selected so that the total system can be developed and managed within the organisation over time. The benefits of developing knowledge objects that are autonomous using common wide-spread applications as methods are two-fold: the knowledge can be used manually without the design automation system, and it is easy to find

people skilled enough to use the very same knowledge the design automation system does - it makes the knowledge more human-readable.

An **Inference engine** (see Fig. 3) is needed to automate the knowledge stored as knowledge objects in the knowledge domain. The inference engine arranges the knowledge objects in an executable order based on their input and output parameters. Two main types of search-based inference engines exist: forward and backward-chaining. A forward-chaining (also called data-driven) mechanism uses the information initially presented to fire all applicable rules. The method has two steps. In the first step, triggered rules are listed. In the second step, an appropriate rule from the triggered ones is selected and fired. After firing the selected rule, all triggered rules are listed again and so on, until no triggered rules are found. If knowledge objects are used to build the knowledge-base, the inference engine searches for knowledge objects with all input parameters known. It then selects one of the found knowledge objects to execute the method defined in that knowledge object to calculate output parameters using the input parameters. When the method has run, the stock of known parameters is updated, and a new search for executable knowledge objects is initiated.

These knowledge objects form the basis for the optimization scheme, as they provide both the objective functions and constraints to the problem within which the optimal product is to be found. In previous work [20] the relevant demands, restrictions and information that controls the design limits have been described.

The automated system, as presented here, can synthesize, simulate and analyse design proposals based on parameter inputs specified in the DoE. The system contains a number of knowledge objects, as defined in Tables 1 and 2. It should be noted that the knowledge objects in the optimization loop are exchangeable and that different software can be excluded or incorporated depending on type of optimization problem.

There are especially two knowledge objects that automates the knowledge of a simulation expert. These are the “Update geometry” and the “Compile ANSA script”. The former use rules embedded in the CAD-model to update the geometrical model based on parameter input from the design of experiment. These rules can result in topological changes of the model, such as the suppression or activation of ribs or holes, replacement of surfaces or referenced sketches. The latter knowledge object automates the knowledge of a simulation expert by applying rules defined in a software developed by one of the authors that configures python scripts that are subsequently executed in ANSATM. The rules are stored in an unstructured way and it is the task of the mentioned inference engine to select and execute rules on demand.

Table 1

Ten knowledge objects used to automate the engineering process in the case of injection moulded polymeric parts.

Name	Input	Output
Update geometry	Connects to CATIA or SolidWorks to update geometry	Updated geometrical model
Export STEP File	Connects to CATIA or SolidWorks to get active model.	STEP file
Compile ANSA Script	Template script	ANSA script for meshing the model, adding load cases and boundary conditions
Run script	ANSA script	FE and Moldex3D models
Run Moldex3D	Moldex3D model	Mould filling simulation results
Get Fibre Orientations	Fibre orientation output file	Converted file for fibre orientations
Create Colour Map	Converted file for fibre orientations	FE colour map for visualization
Convert Fibres to Material	Converted file for fibre orientations	FE material cards based on fibre orientations
Render FE Model	FE material cards, FE model	Complete FE model with fibre orientation

Run FEA	Complete FE model	Simulation results where fibre orientations are considered
Extract results	FEA results	Output parameters to feed the optimisation algorithm

Table 2

Ten knowledge objects used to automate the engineering process in the case of cast components.

Name	Input	Output
Update geometry	Connects to CATIA or SolidWorks to update geometry	Updated geometrical model
Export Geometry Files	Connects to CATIA or SolidWorks to get active model.	STEP file and STL file
Compile ANSA Script	Template script	ANSA script for meshing the model, adding load cases and boundary conditions
Run Script	ANSA script	FE model
Run MAGMA	STL file and template file	Casting simulation results
Get Local Material Data	Casting simulation results	Files with local material data
Create Colour Map	Files with local material data	FE colour map for visualization
Create Material Definitions	Files with local material data	FE material cards based on local material data
Render FE Model	FE material cards, FE model	Complete FE model with local material definitions
Run FEA	Complete FE model	Simulation results where local material behaviour is considered
Extract results	FEA results	Output parameters to feed the optimisation algorithm

2.2 Geometry generator

Within the area of shape optimization, different numerical techniques can be used, e.g. parametrised geometries or mesh morphing techniques. While mesh morphing has the advantage of a strong and direct coupling to the FEM simulation, and has been applied in other approaches [10] a parametrised geometry approach is selected in the current work. An important reason for this is increased flexibility. While morphed meshes are suitable for FEM simulations, they are not easily used in other software's as casting process simulations. By working directly with the CAD model, that can be exported and imported into different types of commercial software, the geometry can be used in practically any type of further simulations, e.g. injection moulding simulations or casting process simulations. Another important reason for this choice is the ability to then generate a finalized CAD-geometry directly from the subsequent optimization, rather than a mesh that needs to be interpreted into a CAD-geometry. The control and handling of the CAD-geometry is in the current methodology handled by the part of the implementation called the Geometry generator.

Within the given frames in the design space, specified in the formalised knowledge objects (e.g. geometrical restraints and freedoms), the geometry generator module is able to generate one or multiple design proposals by controlling a parametrical design within a CAD software. In the current work, the geometry generator is created in Visual Basic™, controlling a parametric template geometry in CATIA™. The template geometry is defined in the knowledge objects, and contains the definitions of the geometrical parameters as well as the specifications needed for positioning the geometry in the subsequent manufacturing simulations, e.g. the size and position of ingate, and the information needed for applying boundary conditions and load cases in the FEA, see Fig. 4. All definitions follow a name convention specified in the knowledge objects.

The geometry generator controls that all the demands and restrictions specified in the knowledge objects are followed, thus keeping the design proposals within the allowable design space. The design geometry is then exported into a suitable file format, e.g. STEP or STL.

Fig. 4. Screenshot of the CAD-model. The model is tagged with parametrized geometry to subsequently generate simulation features in the FEM-model(s). In this case this includes load-cases as predefined DISPLACEMENT, INGATE for form filling, and non-rotational and non-translational boundary conditions (SPC).

2.3 Mesh generator

The geometry exported from the geometry generator is imported into a mesh generator where the mesh for the FEA is created. The mesh generator considers information formalised into the knowledge objects on mesh related demands such as element size, aspect ratio of the elements, number of elements through the thickness of geometries etc. In the current work, the pre-processor ANSA™ is used to generate the FE mesh. In the case of injection moulded polymeric components, the specification of all parameters needed for the injection moulding simulation are also specified in the mesh generator, see Fig. 5. In the case of cast components, the FE mesh is not used for the casting process simulation but required for extraction of local material definitions and the subsequent FEA.

Fig. 5. Screenshot of automatically generated FE mesh. In the real process this view is never seen by the engineers since the software is run in batch mode.

2.4 Manufacturing simulation

2.4.1 Casting process simulation

A casting process simulation template is setup as one of the knowledge objects. The template specifies the positioning of the geometry within the mould as well as possible specification of the ingate system and type of simulation to be performed. Based on specifications in the knowledge objects, simulation settings as material type, alloying content, filling times temperatures can also be specified.

The casting process simulation is able to simulate the entire casting process, including mould filling, solidification, microstructure formation and microstructure-based material characterization models to predict local material properties. The elasto-plastic material characterization models are typically based on the Hollomon or the Ludwigson equation, as further described in previous work [4].

In the current work, MAGMA™ version 5.3 is used for the casting process simulation. In order to generate the local material descriptions needed for the subsequent FEA, the results are first mapped from the casting simulation mesh to the FE mesh from the FE mesh generator using the MAGMALink™ module of MAGMA™. An in-house developed script [4] is applied to generate the elasto-plastic material definitions for the FEA based on the settings specified in the knowledge objects. If specified in the knowledge objects, predicted values of residual stresses, warpage etc. is also included and considered in the optimization loop as initial conditions for the FEA.

2.4.2 Injection moulding simulation

For injection moulded parts, an injection moulding simulation is performed to generate the local material definitions for the part. In this work, MOLDEX3D™ is used for the simulations. In

difference to the casting process simulation, this simulation is performed directly on the FE mesh generated by the mesh generator, see Fig. 6. For glass-fibre reinforced materials, the glass-fibre orientation is simulated. The software also has built-in functionality to predict and export local elastic material definitions based on e.g. the Mori-Tanaka model, and also the effects of e.g. weld lines can be considered to locally reduce material behaviour in specific regions. From the software, linear elastic anisotropic material data can be directly exported to the FE mesh. However, since the output is linear elastic, only the initial phase of deformation characteristics is captured. For most plastics, hardening is imminent even at relatively low loads and it is thus of interest to use non-linear material behaviour. In the present work, the local fibre orientation tensors for each element are exported from MOLDEX3DTM and an in-house code is utilized to establish the non-linear material behaviour by use of the so-called Extended Eshelby-Mori-Tanaka model (Extended EMT). This model make use of the Eshelby tensor for specific geometrically shaped inclusions and incorporate them in the matrix material to mimic a fibre reinforced material. The model will be presented in related work.

Fig. 6. Screenshot of automatically generated Moldex3D model. The arrow indicates the ingate location as specified in the geometry generator.

2.5 FE-file generator

In the FE-file generator, all the information required to perform the FEA is collected, structured, and an input file for the analysis generated. Some of the information is specified in the knowledge objects, as settings for the FE solver, boundary conditions and definition of loads, while some of the required information is obtained from the previous modules, e.g. the FE mesh and the material definitions. Depending on the selected FE solver, the input file will follow different formats and specifications.

2.6 Finite Element Analysis

While the methodology aims to be FE solver independent, in the current work cast parts are analysed using ABAQUS™ while polymeric parts are simulated using LS-DYNA™. The settings of the solver are set in the FE file generator based on the content of the specified knowledge objects. Generally, any type of FE simulation which can be performed in these solvers can also be applied in the current optimisation methodology, e.g. static and dynamic load simulations, thermal loads, crash loads, Eigen frequency analyses etc.

2.7 Result Extraction

When the FEA of the current design is performed, the Result Extraction module reads the FE output files to evaluate the result files based on the objectives specified within the knowledge objects. Results can also be extracted from external knowledge objects, e.g. Excel™-files or MATLAB™-calculations, which enables the use of externally calculated quantitative results, e.g. cost estimations or other geometry dependent manufacturing related aspects. The Result extraction module can thus handle different types of data, which can all be fed as objectives or constraints into the subsequent multi-objective optimization scheme.

2.8 Optimization

In the current approach, a new geometry is created in each iteration of the optimization loop. This makes it possible to apply a wide range of optimization routines. Since manufacturing process simulations may be computationally expensive and time-consuming, each optimization run could entail hours of computation time to find a set of optimal solutions. It is thus highly important that the number of optimization loops required to find the optimal solution is as low as possible.

In industrial product realisation problems, an optimal geometry typically needs to meet several objectives and constraints. Typical objectives, sometimes contradictory, include e.g. minimize weight, minimize cost, minimize stress or maximize fatigue life. In order to be able to handle multiple objectives, a module handling a multi-objective optimization scheme has been implemented. Multi-objective optimization (MOO) of engineering problems using evolutionary algorithms (EA) require several evaluations of each objective within the design space, leading to a large number of simulations runs. Metamodel Based MOO (MB-MOO) is commonly used, where the optimization algorithm is applied on one or several metamodels representing the actual simulations. The basic idea of metamodeling is to create a simplified approximation function of the real model (simulations) in some sampling points within the design space. The metamodels can then be updated based on some convergence criteria in the search for optimal solutions. One approach available in literature is sequential approximative multi-objective optimization (SAMOO). This is necessary in the present context since the shape of the metamodels change abruptly due to updates in e.g. geometry or material [21].

Metamodels are here constructed for each objective by collecting the responses of a set of design of experiment (DoE). As depicted in Fig. 2, the application loop is run based on the number of DoEs to obtain the responses for each DoE. The DoEs provide the input for the geometry generator and at the end of the loop responses are obtained from the results extracted from LS-DYNA™ and ABAQUS™. In this study, Radial Basis Functions (RBF) with a priori bias is used for creating the metamodels. The method has in previous studies shown to have good performance [22].

The number of DoEs is determined based on several factors, where the most important is the number of design variables specified in the knowledge objects. The optimization algorithm is applied on the constructed metamodel. In this study, strength Pareto EA (SPEA2) is used as the

MOO solver. Metamodel based MOO by using a priori RBF and SPEA2 and its efficiency has been presented and investigated in a previous work [23].

3 Discussion

The proposed methodology integrates a multitude of different types of simulations to enable the consideration of heterogeneous microstructure modelling and local material behaviour in an integrated optimization routine. The methodology takes a holistic perspective on the relationship between design and manufacturing aspects, enabling a wide range of objectives and aspects to be considered in the optimization. While no similar approaches for polymeric materials have been found in the literature, other optimization approaches have been proposed for cast components. The approach presented in [7] is focused on evaluating the castability of geometries based on simplistic schematic concepts of geometrical restrictions. This limits its industrial applicability to simple geometries. The current methodology provides more flexibility suitable for generation of complex geometries, while geometrical restrictions can be considered by the selection of parameter constraints. The optimization methodology presented by Cenni et al [9] has clear similarities with the aim of the current approach, but also some significant differences. Cenni et al [9] used a mesh-morphing technique to generate different FEM meshes, which were used first in a thermal simulation representing the solidification simulation and then in a subsequent mechanical simulation with local variations in ultimate tensile strength. The current approach enables the use of full casting process simulations, including mould filling, modelling of microstructure formation, and full integration of local heterogeneous elasto-plastic behaviour, in the optimization routine. This enables a complete coupling of the multi-scale and multi-physical problem of mechanical behaviour of castings. The current approach is also based on a parametric CAD-model rather than mesh morphing, thus the result of the optimization is a CAD model ready to be used for production. In addition, the modular object-oriented implementation of the current approach makes it directly applicable to different types of materials, as shown for cast metals as well as glass-fibre reinforced polymeric materials.

A key in the current methodology is the knowledge objects specified in the initial setup of the optimisation problem. These knowledge objects need to be formulated and formalised based on explicit demands on the product as well as the engineers' own experience and knowledge. While methods exist to address specific simplistic geometrical demands as draw direction [8], such geometrical demands in the current methodology needs to be considered in the specification of the knowledge objects. This enables a more general methodology with possibility to handle more advanced solutions, and various demands that are specific to the type of process under consideration, e.g. the different requirements on draw planes, undercuts etc. in sand casting, die casting and injection moulding. This methodology thus highlights and emphasizes the need for human knowledge, and should be seen as a tool to implement engineering knowledge into products rather than a tool that replaces knowledge.

Simulations are always dependent on the accuracy and physical correctness of the models on which they are based. As manufacturing simulations starts to be used in optimisation schemes, the importance of accurate and reliable descriptions of the material behaviour increases. In future work, the accuracy of the models used within the current methodology needs to be further investigated. The current methodology also gives the possibility to investigate how accurate the material models need to be in order to generate reliable and sufficiently accurate descriptions of material behaviour from an industrial product realisation perspective. This has to some extent been discussed in other studies [7], but further studies which specifically address the consideration of heterogeneous material behaviour are needed.

By formalising information about e.g. geometry, manufacturing, loads and boundary conditions into knowledge-objects which carries information about the demands, objectives and constraints on the part from many disciplines, the concept of structural optimisation is here widened from a strictly geometrical and structural mechanics perspective into an industrial product realisation perspective. The use of knowledge objects in addition enables a methodology where knowledge and information from other areas than engineering can be treated, e.g. economical cost, environmental aspects etc., thus further strengthening the relevance of the methodology in a knowledge-based industrial product realisation context.

The multi objective optimization scheme that is presented herein is based on generic CAD models that are updated based on the knowledge objects concerning criteria for optimal solutions. However, the input to the analyses is in form of e.g. geometry, ingate location and material. Thus, the generation of a metamodel to find a set of optimal solutions cannot be based solely on the first DoE. One approach to overcome this is to use the sequential approximate multi objective optimization algorithm [21], in order to generate several updated metamodels and try and link them to the changes in design space.

In the present work, the methodology and implementation has been presented in detail. In upcoming work, the application of the methodology will be presented, and the numerical effects of performing optimization with and without local microstructure based behaviour further evaluated.

Conclusions

A methodology for multi-objective structural analysis of parts with local microstructure-based variations in material behaviour has been presented. The methodology is based on a KBE perspective, and uses knowledge objects to formalise knowledge about design, material, solid mechanics and manufacturing into a multi objective structural optimisation method. The methodology has been implemented as a prototype software, and is directly applicable for a large variety of structures in cast iron, cast aluminium, and injection-moulded polymeric materials.

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