Real-time structural analysis assistance in customized product design

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***Abstract*— The paper proposes simplification and consequent cost and duration reduction of the customized production workflow, by eliminating the need for traditional structural analysis in the design of the customized product instance from the product family represented by the parametric model. It introduces the concept of so-called compiled FEA (Finite Element Analysis) model which can be used for real-time structural analysis assistance in customized product design. Compiled FEA model is actually ML (Machine Learning) model, consisting of dataset of characteristic product parameters and associated physical properties, selected ML algorithm and a set of its associated hyperparameters. The case study of creating a compiled FEA model for the case of internal orthopedic fixator is provided.**

I. Introduction

Among the new realities of the contemporary production, two of the most prominent are mass-customization [1] and streamlined collaboration-based value chain [2]. Both are facilitated by the trend of manufacturing digitalization and driven by the disrupting technologies such as rapid prototyping, cloud-based storage, enhanced interoperability of diverse enterprise information systems in the value chain and last but not the least, Internet of Things. While latter unleashed the vast, diverse real-time data about operations, logistics and product lifecycle, the former pushed the trend of servitization [3] over the limits. This trend created the opportunities for enhanced collaboration in a product value chain and affordable use of high-end services in the whole production span, starting from structural product analysis to marketing automation and micro-customer segmentation.

In this paper, we explore the practical impact of the above trends to the problem of cost- and time-efficient design of the custom product, based on product family outline generic design, namely a parametric representation of the complex product geometry, with embedded other relevant features, such as exploitation and environment effects, material properties and similar.

Customized product design problem can be reduced to choosing the appropriate values of the prominent features of the product family geometric and structural properties, namely, the product parameters. Those choices are made based on the different criteria, including customer requirements, part and material market cost and availability, product pricing policies, exploitation conditions and others. The set of the product's parameters combined with the other fixed properties is called a parametric product model.

In any stage of the custom product design, the single design instance may be validated. Such validation can be relatively simple and quick (for example, inspection of the product visual properties by the customer) but sometimes, very troublesome and significant cost-incurring, such as testing of the product instance physical properties and its integrity in the exploitation conditions. The latter is often carried out by Finite Element Analysis (FEA) [4].

FEA could help to calculate the physical properties of the product in exploitation, such as occurrence of critical stresses and deformations in the product areas.

Unfortunately, the structural analysis of the customized products is often removed from the design pipeline due to the mass-customization related time and cost pressures (FEA software annual subscription rates are as high as tens of thousands of dollars), long duration (complex product FEA alone, even without considering FEA model preparation, can last for hours, even days), high-level expertise requirement and consequently, high cost of the service.

A. *Concept of solution*

In response to the above issues and opportunities, we are assuming the following scenario. A manufacturing company maintains the parametric model of the product family design. Upon customer request, the designer needs to create this model's instance, so this instance meets all the given requirements. Instead of launching the FEA on the specific instance, the designer is assisted in a real-time by the software which is using the model we call the "compiled" generic FEA model.

Compiled FEA model is based on the physical properties (for example, level of mechanical stresses in critical product areas, product mass and similar) of the number of "characteristic" data instances. Characteristic data instances are relatively large collection of product model parameter (lengths, widths, distances, material properties, etc.) values in the selected regions, associated with previously calculated mechanical features (such as stresses and product mass). Those properties are calculated once, for the whole product family and then used to fit the prediction function, derived by using a Machine Learning (ML) algorithm [5].

Therefore, compiled FEA model is actually serialized ML model and it involves dataset with characteristic instances, selected ML algorithm and best performing hyperparameters.

From the performance point of view, predicting the physical properties based on the specific set of the parametric model values is trivial and such service can be executed in a real-time, during the custom product design. More important, no additional cost is incurred.

B. *Research questions*

The above scenario introduces several hypotheses which are being validated during the research reported in this paper:

- FEA software can be used to create a dataset relevant for developing a compiled FEA model, with representative values of the selected product design parameters;
- Based on the above dataset, ML models can be developed for predicting physical properties of the custom product which was instantiated by selecting the appropriate design parameters with sufficient accuracy;
- Multi-criteria optimization methods [6] can be used to identify all local optimums, namely, to identify the characteristic instances from the dataset that are associated with best combination of physical properties.

C. *Methodology*

In this paper, we propose the solution that aims to confirm only first two hypotheses, while the multi-criteria optimization methods are considered out of scope. The solution is developed by using the following methodology:

First, design-of-experiment feature of the selected FEA tool is used to create the dataset of characteristic product instances, based on the selected product family parametric model. In this research, the dataset will include several design parameters (product dimensions) and two physical properties – maximal equivalent stress over the product and product mass.

Second, ML prediction model is created by fitting the selected ML algorithm with the dataset above, where design parameters are considered as input and physical properties as output features.

Prediction model is developed by using Python programming language. Prediction model development follows the typical ML pipeline, namely distribution and correlation analysis, feature selection, algorithm selection and optimization of the selected algorithm hyperparameters.

II. PROPOSED SOLUTION

The compiled FEA model is developed for the case of orthopedic device – internal fixator, used in subtrochanteric fractures of thigh bone (femur).

This is the case of highly customizable product which needs to be fitted to the different requirements arising from patient physical and physiological properties, one of many different types of fractures, etc. The process in which this fitting is carried out is out of the scope of the research behind this paper.

The fixator parametric model has been created by using SolidWorks CAD software. In this case, it is defined by 6 relevant geometry parameters and fixed design. The illustration of the model is provided on Figure 1 below.

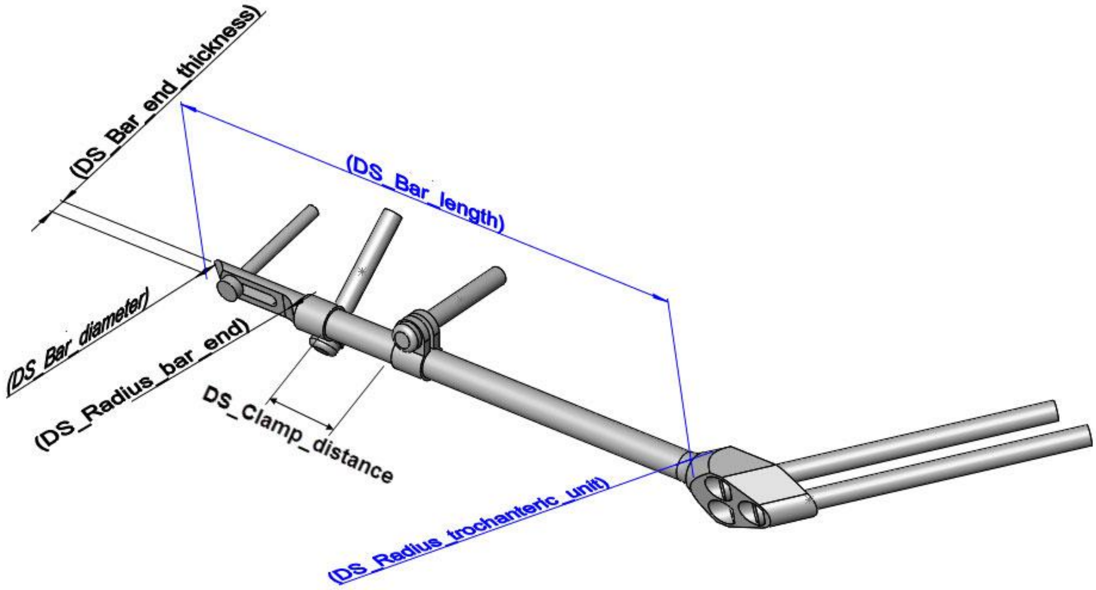

Figure 1. Parametric model of the internal fixator

Design Explorer module of ANSYS FEA software, which was used for calculation, features the design-of-experiment functionality. Namely, it is capable to generate the set of values of input parameters that defines the collection of characteristic product instances. These values are then used to create the CAD model instances in SolidWorks and send them back to ANSYS for calculation of physical properties.

Created dataset is used as input to the typical ML pipeline. The dataset counts 88 rows. Small number of data instances was used in a case study for the practical reasons (single instance calculation of physical properties by ANSYS takes time) as well as because of representativeness of data generated by design-of-experiment feature.

First, analysis of data distribution and correlation was carried out.

Distribution of the input variables was found balanced which means that the design-of-experiment tool has identified representative data. This is very important because it implies that the risk of overfitting is significantly reduced.

The distribution of mass and stress features data appeared neither Gaussian nor exponential. This implied that parametric ML algorithms would probably not provide a good fit.

The correlation analysis was performed by considering Pearson linear correlation and Spearman monotonic interaction coefficients for the features' pairs. It was found that there existed significant linear correlation between d2 (DS_bar_length, see figure 1 above) and both output features (Pearson: 0.897, -0.61), as well as d5 (DS_radius_bar_end) and stress (-0.666). Notable linear correlation is found between d3 (DS_bar_diameter) and mass (0.399). As for the monotonic interaction between features, it is significant between d2 and mass (Spearman 0.943), as well as d5 and stress (-0.674) and notable between d2 and stress (-0.554), as well as d3 and mass (0.261).

To complement the correlation analysis, a Recursive Feature Elimination (RFE) method is applied with goal to explore the relevance ranking of the subsets of the input features, by using the selected algorithms, namely simple linear regression, Random Forest and Gradient Boosting regressors.

In addition to d2, d3 and d5 which have been already proven as relevant, RFE with the latter two regressors had uncover the relevance of d1 (DS_clamp_distance) for stress. As outcome of the correlation analysis, input features d4 (DS_bar_end_thickness) and d6 (DS_radius_trochanteric_unit) had been removed from the dataset.

In the following step, the selected ML algorithms were fitted with the dataset and the outcomes of the resulting models' accuracies were compared. K-fold cross validation (k=5) was used for validation and Negative Mean Absolute Error (NMAE) was used as indicator.

Testing produced the results as shown on Figure 2 below. Row 0 shows NMAE for mass output feature, while row 1 shows NMAE for stress.

	LinearRegression	KNeighborsRegressor	SVM	DecisionTree	RandomForest	GradientBoosting
0	-0.004045	-0.009694	-0.024171	-0.002122	-0.001973	-0.001057
1	-39.050563	-64.675932	-61.707028	-16.766466	-14.885934	-14.252158

Figure 2. Negative mean absolute errors of the fitted models

Obviously, Gradient Boosting algorithm [7] was best fitted with data, producing NMAE well within standard deviation (0.03 for mass and 88.2 for stresses) and certainly within the limits of acceptable error in structural analysis of products of this type.

Finally, Grid Search method [8] was used for optimization of hyperparameters. Unfortunately, it did not produce significant improvements in the accuracy metrics.

To conclude, the considered research hypotheses have been convincingly confirmed in a case study. The developed ML model can be serialized as compiled FEA model and used in hypothetical CAD tool add-on – container for compiled models of selected product families. CAD model enriched with this add-on can provide real-time structural analysis assistance of custom product design and thus, significantly reduce its time and cost.

III. Discussion

The Figure 3 depicts the design of the infrastructure for the implementation of the proposed solution for real-time assistance in customized product design.

The process starts with the development of parametric model and design of experiment. Design of experiment data is used to develop a compiled FEA model, as described above. It is then deployed as a web service resource. Web infrastructure facilitates:

- the deployment of compiled FEA models and parametric models,
- management (including versioning) of non-geometric model parameters (in the above example, maximal equivalent stress over the product and product mass)
- end user authentication and tracking logic and
- a business model (subscription based, pay per view, etc.) of choice.

It should be exposed by REST API with authentication and key verification functionalities.

Client is considered as add-on to one of the commonly used CAD platforms. Add-on facilitates:

- user login,
- definition and serialization of non-geometric model parameters (e.g. exploitation and environment effects, material properties)
- display of user interface with the addon toolbox and visualization of predicted physical properties
- synchronous REST calls to a web service using associated compiled FEA model, where input is current set of parameters (geometric and non-geometric) and output – predicted physical properties.

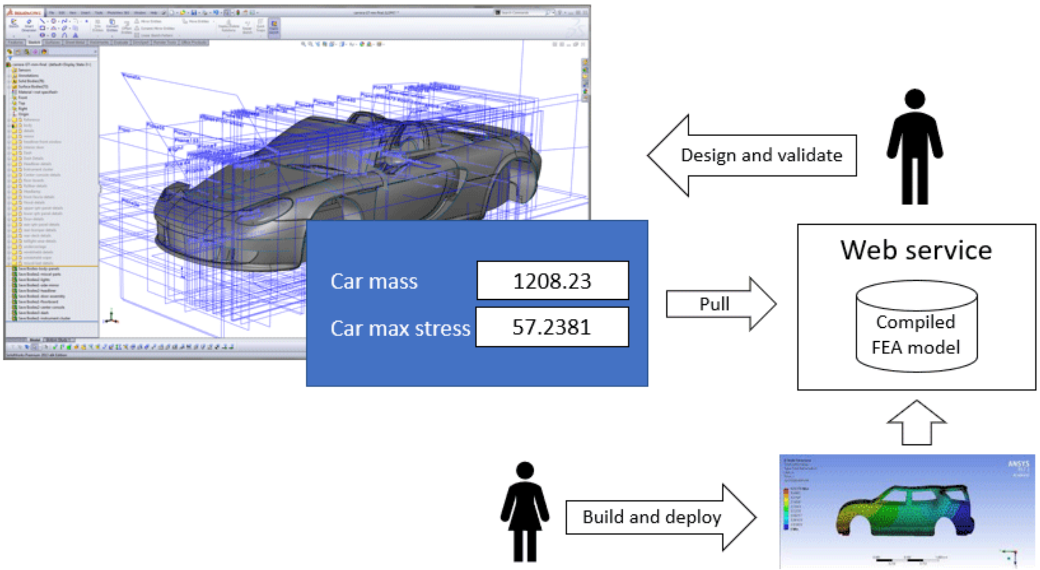

Figure 3. Scenario and hypothetical assistance tool

IV. CONCLUSION

Mass-customization trend, implying the need for design and manufacturing of custom product designs with efficiency near to mass-production is a new industrial reality. This trend highlights the challenges in manufacturing and custom product design domains.

The proposed solution aims to solve the problem of long and expensive custom product design process, and in specific, the need for a special (expensive) expertise in building FEA models, lots of computational resources needed and expensive FEA software. The solution assumes the use of so-called compiled FEA model, offering approximated values of non-geometric parameters, vital for the custom product design. The use of compiled FEA model during geometric parameter tuning facilitates real-time review of the critical non-geometric features and immediate assessment of the designed product physical properties.

Moreover, the proposed solution creates opportunities for new collaborative business models, in which the roles of CAD and FEA specialists are separated across the enterprises and FEA can be implemented as online service.

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