Computers in Industry 91 (2017) 45–61

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

A priori evaluation of simulation models preparation processes using artificial intelligence techniques

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ARTICLE INFO

Article history:
Received 8 December 2016
Received in revised form 14 April 2017
Accepted 6 June 2017
Available online xxx

Keywords:
Process evaluation
Digital Mock-Up preparation
Artificial intelligence
Machine learning
Knowledge formalization

ABSTRACT

Controlling the well-known triptych costs, quality and time during the different phases of the Product Development Process (PDP) is an everlasting challenge for the industry. Among the numerous issues that are to be addressed, the development of new methods and tools to adapt to the various needs the models used all along the PDP is certainly one of the most challenging and promising improvement area. This is particularly true for the adaptation of Computer-Aided Design (CAD) models to Computer-Aided Engineering (CAE) applications, and notably during the CAD models simplification steps. Today, even if methods and tools exist, such a preparation phase still requires a deep knowledge and a huge amount of time when considering Digital Mock-Up (DMU) composed of several hundreds of thousands of parts. Thus, being able to estimate a priori the impact of DMU adaptation scenarios on the simulation results would help identifying the best scenario right from the beginning. This paper addresses such a difficult problem and uses artificial intelligence (AI) techniques to learn and accurately predict behaviours from carefully selected examples. The main idea is to identify rules from these examples used as inputs of learning algorithms. Once those rules obtained, they can be used on a new case to a priori estimate the impact of a preparation process without having to perform it. To reach this objective, a method to build a representative database of examples has been developed, the right input (explanatory) and output (preparation process quality criteria) variables have been identified, then the learning model and its associated control parameters have been tuned. One challenge was to identify explanatory variables from geometrical key characteristics and data characterizing the preparation processes. A second challenge was to build a effective learning model despite a limited number of examples. The rules linking the output variables to the input ones are obtained using AI techniques such as well-known neural networks and decision trees. The proposed approach is illustrated and validated on industrial examples in the context of computational fluid dynamics simulations.

1. Introduction

The Product Development Process (PDP) relies on a multitude of activities such as design, sizing, analysis, product optimization, process simulation or prototyping. Each activity is often based on an adapted Digital Mock-Up (DMU) used to model the product with more or less details. The preparation process of an original DMU to a representation adapted for a given activity is still a very challenging issue. It often requires a succession of operations which are based on different tools driven by many control parameters. Today, even if the methods and tools used to perform these operations exist, following such a preparation process strongly relies on the knowledge of the experts that is not fully formalized. This lack of formalization and the associated lack of knowledge on the performance of a given preparation process induces numerous iterations between the original model and the model prepared for an activity. Thus, being able to estimate a priori the cost and quality of a given preparation process will help optimizing the transfer between Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) models. As a consequence, the PDP will be shortened and the over-quality avoided.

Today, even if commercial software does incorporate some functionalities dedicated to the adaptation of CAD models to CAE applications, the preparation process still requires a deep knowledge and a huge amount of time when considering Digital Mock-Up (DMU) composed of several hundreds of thousands of

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http://dx.doi.org/10.1016/j.compind.2017.06.001
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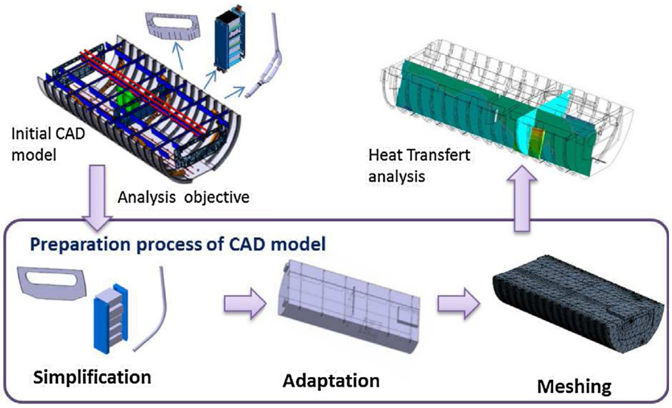

Fig. 1. Main stages of CAD model preparation (application to CFD analysis).

parts. The preparation process consists of three main steps: simplification, adaptation and meshing (Fig. 1).

The CAD model simplification eases the meshing and simulation steps by removing items and modifying the geometry. Simplification techniques are detailed in Section 2.1. The adaptation steps consist in extracting faces for meshing and in identifying the surfaces supporting the boundary conditions. The CAD model meshing allows the numerical analysis of the problem by approximating a geometry with more or less small and complex elements (e.g. triangles, tetrahedra, hexahedra) depending on the available computing time and the expected accuracy. The preparation process can be described and modelled by a set of operations, a sequencing and a set of control parameters. For each operation, the user adjusts one or more parameters (e.g. the size of mesh elements, the level of simplification, the list of sub-assemblies to remove). Therefore, for a given simulation objective, there exists many preparation processes. Today, the sequence of operations and the associated control parameters are selected by the experts who try to minimize the impact of the adaptation on the results while minimizing the preparation costs. Those costs are strongly correlated to the time spent by the expert on the different tasks.

They exist many tools and operations to simply a CAD model, Section 2.1 presents the main simplification techniques applied to our case study. However, the criteria used to select which operations and which parameters are to be used are not fully formalized and the effects not always mastered. Section 2.2 introduces methods to evaluate the impact of a simplification on the results of an analysis. However, there is a lack of methods to a priori estimate the impact of a simplification on the quality and accuracy of a simulation.

Therefore, the aim of this work is to define a new approach to estimate a priori the quality of a preparation process. In this way, the analysts can test different adaptation strategies and thus identify the best one with respect to a given simulation objective. Of course, this does not exempt the analysts to make the numerical simulation at the end, but only one time following the preparation process considered as the best. The proposed approach is based on the use of artificial intelligence (AI) techniques [1] for the evaluation of preparation process quality. The quality of a preparation process could be evaluated by orders of magnitude of analysis errors, preparation duration and analysis duration. Amongst AI techniques, supervised learning techniques are able to estimate output variables from carefully selected examples without knowing rules that link input and out variables. Variables to predict can be discrete values that are divided into several classes. So, the retained AI techniques must be able to predict a discrete output variable from a set of input variables. Classifiers

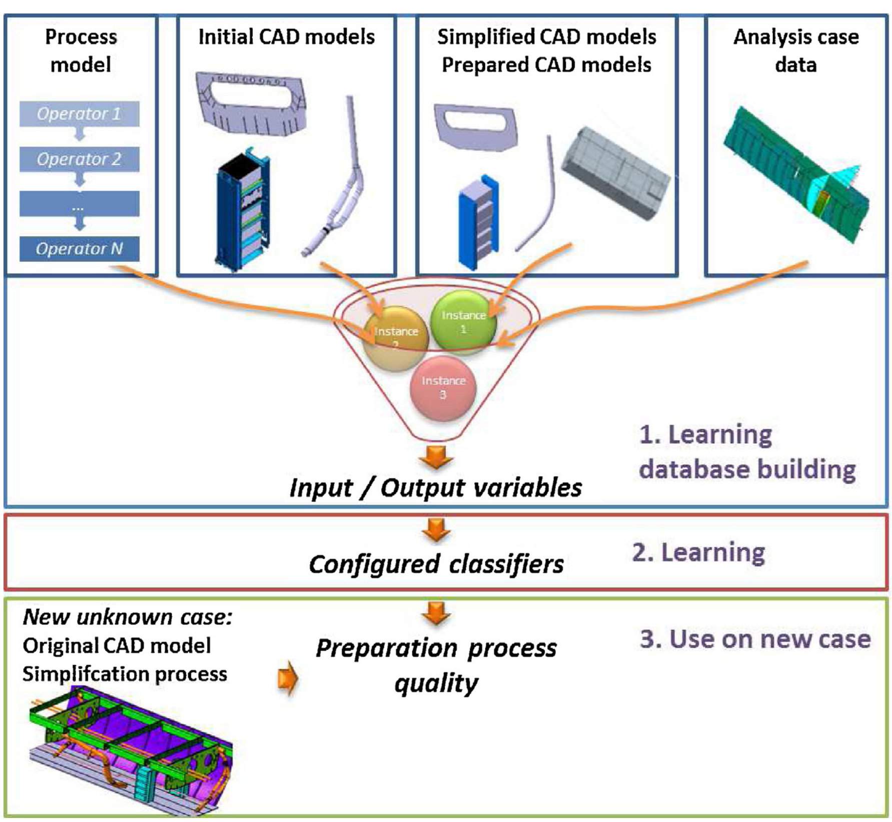

Fig. 2. General approach for preparation process evaluation by using machine learning techniques.