

Thesis title: A Coupled Machine Learning and a Fast Inverse Method for the Analysis of Metal Forming Process Parameters: Application to Clinching Process

The use of multi-materials to achieve lightweight complex structural assembly designs is continuously increasing over the last decade, due to their abilities of reducing the weight while enhancing the mechanical performances [1]. There exist several sheet-metal joining processes for the design of advanced lightweight structural assemblies. The cold-forming process clinching allows to join two or several metallic sheets based on a force-fitting connection. Therefore, no additional components (such as rivets) are needed to realize the assembly, making the process environmentally friendly and economical. Moreover, compared to other joining processes, clinching allows a fast and efficient way to join different metals of variable sheet thicknesses allowing wide industrial applications in the transport systems, aeronautics, automotive, etc. [2].

This thesis deals with the development and the extension of an original Inverse Method for the fast simulation of the clinching process. This Inverse Method was developed by the supervisor for the simulation of sheet metal forming [3-4], is based on the knowledge of the final workpiece where assumptions are made regarding the action of the tools (punch and die) at the end of the forming process. Logarithmic strains and total deformation theory of plasticity will be considered and the equilibrium of the final workpiece leads to a set of nonlinear equations which can be solved by different techniques such as the Newton–Raphson static implicit approach, the dynamic relaxation method or the dynamic explicit algorithm. It is proposed here, to extend the Inverse Method to make it able to simulate the clinching of two metallic sheets of different materials and variable thicknesses. The final clinching joint external layers are assumed to be known as well as the initial sheets, hence the method will allow the estimation of the material flow and the final thicknesses. A solid-shell finite element [5] based on the discrete Kirchhoff theory will be developed in order to capture the large elastoplastic strains locally during the clinching process using a single element in the mid-plane of the shell contrarily to the standard continuum. The numerical developments in the framework of the present PhD thesis will concern the review and alleviation of numerical locking phenomena generally encountered in the standard solid-shell finite element formulation [5].

To achieve a high quality of the clinching assembly, process parameters must be optimized [6] to enhance the quality-relevant geometrical joint performances, like the neck and interlock thickness. To this purpose, the application of machine learning techniques has shown to be effective in determining a set of solutions including a set of several design alternatives. Among these techniques, the coupling of Deep and Reinforcement Learning appears to be a promising tool for the identification of optimal solutions in various domains [7,8]. Hence, in this work, they will be implemented and used to determine clinching tool and process configurations, while the Inverse Method will be regarded as the “black box” solver for the clinching simulation. The resulting automatic design tool is original since it will be considered as a semi-supervised machine learning algorithm to identify optimal clinching process parameters.

The developments in this thesis will be done starting with Python coding, and then will be implemented in the open source software CalculiX (www.calculix.de). Indeed, this software offers numerous advantages such as contact algorithms and various time integration schemes.

For the validation of the model, several benchmarks from the NUMISHEET and NUMIFORM international conferences will be evaluated and the results compared to those obtained using commercial code LS-DYNA and those from the literature.

This thesis subject is original and has never been addressed by the international scientific community of metal forming; hence the developments in this thesis will surely allow the publication of several articles in peer-reviewed international journals.

Keywords: Metal Forming; Clinching Process; Finite Element; Inverse Method; Machine Learning; large strains; plasticity.

Background of candidate: Expected candidate should have basic knowledge of sheet metal forming, finite element modeling and basics of programming.

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