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A hybrid multi-fidelity approach to the optimal design of warm forming processes using a knowledge-based artificial neural network

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Abstract

In this paper, a hybrid multi-fidelity optimization approach based on a knowledge-based artificial neural network (KBNN) was used to determine the optimal heating strategy in warm forming processes. First, a less costly, but less accurate isothermal finite element analysis (FEA), which neglected the complex heat transfer between the part and tooling elements, was performed to obtain overall knowledge about the effect of temperature on forming performance. Then, a small number of more accurate and expensive (i.e., longer computational time) non-isothermal FEA results were utilized in an artificial neural network (ANN), along with the prior knowledge from the isothermal FEA, to improve the accuracy in defining the non-linear relationship between the design variables (i.e., regional temperatures on the tooling) and the response (i.e., part depth value before failure). The accuracy of the non-isothermal FEA was validated by comparing its prediction results to the experimental findings. This approach was demonstrated for forming a rectangular cup, where it offered a rapid and accurate recommendation of the optimal temperature distribution on the tooling elements for improved formability. The individual and interaction effects of the regional temperatures on formability were also evaluated in detail by constructing the response surfaces near the optimal design point using the multi-fidelity system developed. Finally, a comparison of the temperature and thickness strain distributions on the formed parts was made under various operating conditions, to acquire detailed information on the deformation characteristics of the material.

Keywords: Warm forming; Lightweight materials; Multi-fidelity optimization; Response surface; Artificial neural network

1. Introduction

Reducing the weight of vehicles is one of the primary means by which their fuel consumption and hazardous air pollutants can be reduced. The portability of various products such as appliances, computers, machinery, etc. can be also improved by the realization of lightweight structures. Thus, there has been an increasing trend toward the use of lightweight materials (i.e., aluminum, magnesium, advanced high strength steel (AHSS), and composites) in automotive, aerospace, appliance, and energy industries. Due to the inferior formability of some lightweight materials such as aluminum and magnesium at room temperature, however, the justification of using lightweight structural parts to replace steel is very difficult and questionable in the context of conventional fabrication processes like forging and stamping.

As one of the technologies that enables improvement in the formability of lightweight materials, the warm forming process is attracting more and more interest from industries. It was reported that at elevated temperature levels (200–350 °C) aluminum–magnesium alloys (0–6.6% Mg) achieved an elongation up to 300% [1]. Many preliminary studies have proven a significant increase in formability with 5XXX and 6XXX series of aluminum and AZ31 and AZ61 magnesium alloys [2–4]. A significant effect of both strain rate hardening and strain hardening on formability was confirmed by some early experimental studies. The improvement of formability at

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elevated temperatures was attributed mainly to the enhanced strain rate sensitivity that comes with increasing temperature [5,6].

Attempts on warm forming of lightweight materials have not, however, gone beyond lab-scale experiments on simple cups and a few prototype trials in the industry, because of various underlying unknowns. These unknowns include the effect of temperature distribution and control on the forming limits and lack of understanding of complex interface conditions. To broaden the fundamental understanding of the warm forming mechanism and to shorten product and process design lead time, finite element analysis (FEA) techniques have been tried in recent decades. The effectiveness of using FEA for warm forming analysis has been verified through case studies where FEA results were compared with experimental findings for simple part cases [7–10]. In addition, optimization techniques, such as sensitivity analysis [11,12], genetic algorithm [13], and artificial neural network (ANN) [14] have been increasingly applied to metal forming process design and control in combination with FEA. When such optimization methods were used for the industrial-size warm forming FEA models, however, it was recognized that the time required to complete such simulations could be impractically long due to the large number of design variables and the complex features of the full scale models. Thus, in order to exploit the benefits of FEA as a virtual experimentation and/or prototype process effectively, and to eliminate costly trial and error procedures of current practices, alternative process and tooling optimization techniques become necessary.

To attempt to achieve computational efficiency, while preserving reliability in design optimization problems, there has been some research on the multi-fidelity technique. This combines results from a small number of expensive and accurate high-fidelity analyses with those from a large number of cheaper and less accurate low-fidelity analyses. Hutchison et al. [15] coupled a detailed aerodynamic model with a simple algebraic model in the optimization of a high-speed civil transport (HSCT) wing. They first utilized the simple model to estimate the drag components. Then, the deviation of the responses from the detailed model was corrected by a constant scaling function obtained at the nominal design point. This approach allowed the optimization to proceed effectively without excessive computational expense. Heftka [16] demonstrated a global-local approximation method with a simple beam example. In his study, a crude FEA model captured the general trend of a buckling load with respect to the cross sectional area. A linearly varying scaling factor calculated using the derivative of a more refined FEA model enabled the inexpensive and reliable predictions of the bucking load in a wider range of design space. Neural network techniques were also used to correlate the low- and the high-fidelity models. Watson and Gupta [17] used a neural network to predict the differences between the two models in microwave circuit design. Leary et al. [18] developed a knowledge-based artificial neural network (KBNN) incorporating the low-fidelity analysis result into the network structure. Using the knowledge acquired from the cheap function when training the network, an improved level of accuracy could be achieved over the entire design domain using only a small number of expensive results.

This paper attempts to develop a hybrid multi-fidelity system to determine the optimal temperature distribution of tooling elements in a rectangular cup forming process. Less accurate and less costly isothermal FEA was used as the low-fidelity model, and was combined with expensive and accurate non-isothermal FEA (i.e., high-fidelity model) to reach the optimal design point in a short computational time. The non-linear relationship between the design variables (i.e., regional temperatures on the tooling) and the response (i.e., part depth value before failure) was established using (a) a polynomial function and (b) a KBNN [18]. The performance of each algorithm was evaluated by comparing the approximations from the developed multi-fidelity systems to the high-fidelity analysis results. The effect of regional temperatures on forming performance was investigated by constructing the response surfaces near the optimal design point. In addition, detailed deformation characteristics of the material at different temperature conditions were further discussed from the temperature and thickness strain distributions on the formed parts.

2. Development of a multi-fidelity system

The design problem of this paper is the optimization of warm forming temperature distribution. We wish to maximize the formability of an aluminum alloy by varying the temperature distribution on the tooling system in a range of 25–350 °C. Since the classical optimization procedures that are based on an iteration algorithm require hundreds of high-fidelity analyses to obtain reliable responses, we cannot afford the high computational cost for complex design problems such as a warm forming process. Thus, a multi-fidelity system, utilizing the less accurate but efficient low-fidelity analysis in approximating the responses of the high-fidelity model, was developed. The objective function in this study was the achievable part depth value before failure. This original objective function $F(\mathbf{x})$ from the high-fidelity non-isothermal FEA model could be approximated to $\hat{F}(\mathbf{x})$ using the low-fidelity isothermal FEA model as follows:

$$\hat{F}(\mathbf{x}) = \hat{F}(\hat{f}(\mathbf{x}), \mathbf{x}) \approx F(\mathbf{x}), \tag{1}$$

where $\hat{f}(\mathbf{x})$ is the response of the objective function by the low-fidelity model and $\mathbf{x}$ represents the design variables. Then, it was used instead of the original function to reduce the number of high-fidelity analysis in the optimization procedure.