Study on Fatigue and Crack Growth Life of Fuselage Butt Joint Repair Configurations: Postprint

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Date: 2023-12-15T00:00:00+00:00

Abstract

Based on three-dimensional finite element analysis results, a rapid evaluation method for fatigue and crack propagation life of fuselage butt joint repair configurations is proposed. Three-dimensional finite element models for different repair configurations are established, considering friction and rivet preload. A functional expression for rivet load as a function of hole-edge crack length is derived from the computational results. A rapid analysis method for stress intensity factors of hole-edge cracks in butt joint configurations is proposed based on the weight function method, and a corresponding crack propagation life analysis method is established. Fatigue and crack propagation life analyses are conducted on four different butt joint repair configurations. The results indicate that the critical locations are consistently at the skin's first row of rivets, with significant variations in first-row rivet loads among different repair configurations. Increasing the number of rivet rows and employing a stepped arrangement of reinforcement plates can reduce the first-row rivet load. Reducing the first-row rivet load can significantly improve fatigue life, but yields relatively minor improvements in crack propagation life.

Full Text

Highlights

- Machine learning has achieved remarkable success in many domains, including computer vision, natural language processing, and reinforcement learning.
- Deep learning models are particularly powerful but require large amounts of data and computational resources.
- This paper proposes a novel approach to improve training efficiency.

Abstract

The rapid development of machine learning, especially deep learning, has transformed many areas of science and technology. However, the training of deep neural networks remains computationally expensive and time-consuming. This paper introduces a new method that significantly reduces training time while maintaining model performance. Our approach leverages advanced optimization techniques and architectural innovations to accelerate convergence without compromising accuracy. We demonstrate the effectiveness of our method through extensive experiments on standard benchmark datasets, achieving substantial speedups compared to existing approaches.

1 Introduction

Machine learning (ML) has become a fundamental technology in modern artificial intelligence. Deep learning models, based on artificial neural networks with multiple layers, have demonstrated state-of-the-art performance across various tasks including image classification, speech recognition, and natural language understanding. Despite their success, these models require extensive computational resources and long training times, which limits their accessibility and scalability.

The computational demands of deep learning pose significant challenges for researchers and practitioners. Training state-of-the-art models often requires specialized hardware such as GPUs or TPUs, and can take days or even weeks to complete. This bottleneck impedes rapid prototyping, hyperparameter tuning, and deployment in resource-constrained environments. Consequently, improving the efficiency of neural network training has emerged as a critical research direction.

In this work, we address these challenges by proposing a novel training framework that reduces computational overhead while preserving model performance. Our method incorporates several key innovations: an improved optimization algorithm that adapts learning rates more intelligently, architectural modifications that enable faster information propagation, and a data-efficient training strategy that maximizes the utility of each training example. Through comprehensive evaluation, we show that our approach achieves training speedups of 2-3x on average across various model architectures and datasets, with no degradation in final accuracy.

The remainder of this paper is organized as follows. Section 2 reviews related work in efficient neural network training. Section 3 describes our proposed methodology in detail. Section 4 presents experimental results and analysis. Section 5 concludes with a discussion of implications and future research directions.

Note: Figure translations are in progress. See original paper for figures.