LAMBDA Technologies Group

Diffraction Notes

www.lambdatechs.com

Issue No. 53 Improving Component Life and Performance 2024

HARNESSING NEURAL NETWORKS FOR ADVANCED SURFACE ENHANCEMENT OPTIMIZATION

INTRODUCTION

Manufacturing processes inherently produce residual stresses, profoundly impacting the functionality and longevity of finished components. These stresses, resulting from processes such as forging, casting, heat treatment, machining, and welding, should be considered in engineering design. The field of residual stress design aims to comprehend, manage, and potentially harness these stresses to enhance the overall performance and lifespan of engineered parts.

Surface enhancement is a cost-effective and efficient way to introduce beneficial compressive residual stress, improving component performance beyond the inherent stresses from manufacturing processes. These treatments provide manufacturers with an attractive option to enhance product quality without resorting to more extensive changes like alloy substitution or part redesign. By implementing such methods, companies can achieve significant improvements in part performance while maintaining their existing production processes, thus saving time and resources. By optimizing surface treatment parameters, the engineer can take full advantage of the performance effects of compressive residual stresses.

SURFACE PROCESS OPTIMIZATION THROUGH LARGE DATASETS AND NEURAL NETWORKS

Surface enhancements, such as shot peening, low plasticity burnishing (LPB®), and laser shock peening (LSP), play a crucial role in extending fatigue life and increasing damage tolerance and stress corrosion cracking resistance of components. The compressive residual stress and surface finish produced by a mechanical surface treatment is the result of a myriad of process variables. Shot peening, for example, includes media type, shot stream velocity, air pressure, impact angle, and the physical and metallurgical properties of the component, just to name a few. A major factor is the general interaction between the material properties of the component and the kinetics of the process. These interactions significantly impact the resultant residual stress field produced by the process, which is critical to the effectiveness of a surface treatment.

A common approach for parametric development of a surface treatment is to use experimental design techniques, like the Taguchi method, to systematically vary process parameters and analyze their effects on residual stress. The usefulness of these techniques can be limited due to several issues, including inability to both handle complex interactions and properly account for cross-term effects between factors, which can be important in surface treatment processes.

Neural network modeling offers several advantages for optimizing surface treatment parameters. Surface treatments can involve complex, non-linear relationships between multiple process variables and the resulting residual stresses. Neural networks excel at capturing these intricate, multidimensional relationships that may be difficult to model analytically. Once trained, they can be used to “reverse-optimize” process parameters. This means engineers can specify desired residual stress profiles and use the network to determine the optimal treatment parameters to achieve those results. Neural networks can rapidly evaluate many combinations of process variables to find optimal settings and can be retrained or fine-tuned as new experimental data becomes available. This allows the optimization model to continuously improve and adapt to different materials or treatment variations over time. Using high resolution residual stress data as input, the complex interactions of a multivariate surface treatment process can be understood. These advanced techniques provide a predictive residual stress leading to more accurate and efficient optimization strategies.

THE ROLE OF PROCESS AND MATERIAL PARAMETERS IN SHOT PEENING

Lambda Technologies conducted a study to explore the complicated interplay of shot peening parameters and material properties on the surface roughness and residual stress field of a widely used high-strength steel. A comprehensive dataset of residual stress depth profiles

LAMBDA Technologies Group

Diffraction Notes

www.lambdatechs.com

Issue No. 53 **Improving Component Life and Performance** 2024

was generated by systematically varying heat treatments and peening parameters. Specialized x-ray diffraction measurement systems were employed to obtain the detailed, high-resolution residual stress distributions necessary for optimization through neural network analysis. High-resolution residual stress depth profile data allow the models to capture subtle variations in stress distribution, leading to more reliable predictions. This level of detail is particularly important when optimizing for specific attributes, such as maximum compressive stress or depth of compression, which are critical for component performance under operational stresses. Figure 1 presents a few examples of these high-resolution residual stress depth distributions, each resulting from a specific set of peening parameters and material properties.

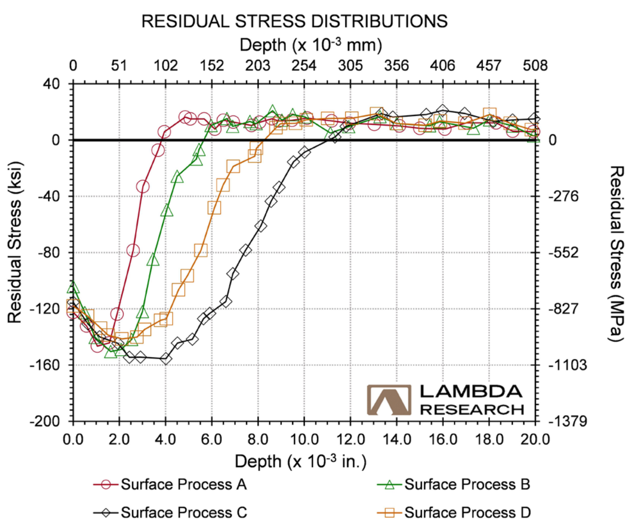

Figure 1

By utilizing neural networks to analyze these detailed distributions and their corresponding process parameters, engineers can gain a deeper understanding of how to fine-tune the shot peening process for optimal results in various applications. A neural network fitting and prediction study was conducted to model the relationships between the various parameters and the resulting residual stress and peak width profiles. The neural network models, an example of which is shown in Figure 2, showed promising results in predicting residual stress and peak width profiles based on process input parameters. Model error analyses were performed, with the models demonstrating reasonable accuracy in predicting profiles for both included and withheld data sets. These results suggest the potential for using neural network modeling to predict shot peening outcomes in various steel materials.

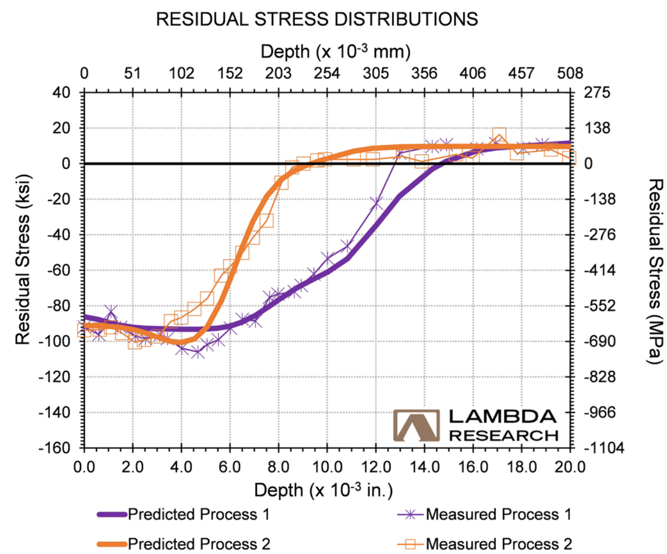

Figure 2

CONCLUSION

In conclusion, the optimization of shot peening and other surface enhancement processes is greatly improved by the use of large datasets and neural networks. By understanding the interactions between material properties and processing variables, engineers can develop more effective and efficient surface enhancement techniques. High-resolution residual stress data play a pivotal role in this optimization, providing the detailed insights needed for accurate modeling and prediction.

Lambda Technologies is uniquely suited to quickly and accurately produce and analyze large datasets due to our extensive experience and specialized measurement systems. Our advanced systems and methodologies allow us to efficiently conduct experiments and gather high-quality data. Additionally, we have an extensive catalog of experimentally determined data from a wide range of materials, providing a solid foundation for developing robust predictive models. As surface treatment technologies continue to evolve, the integration of advanced data analysis techniques, supported by Lambda Technologies' expertise and resources, will be key to unlocking new levels of performance and reliability in engineered components.