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ON MODEL ORDER REDUCTION IN SIMULATIONS OF LASER SHOCK PEENING

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Abstract: *Laser shock peening (LSP) is a modern but already established approach to improve the strength and fatigue resistance of components by hardening their surface. LSP is based on the use of a high-energy laser to generate mechanical loading of the component surface. Compared to standard peening techniques, e.g., shot peening, LSP allows for precision surface treatment since the individual laser spots can be positioned with an accuracy of the order of 0.1 mm. Furthermore, the laser energy ($\sim$ 1 J) as well as the spot size ($\sim$ 1 mm) are tunable parameters. This process tunability allows for component- and material-based optimization that can be accelerated through simulations. However, simulations of LSP treatment of real-life components are time consuming in such a way that it disallows their direct usage in process optimization. In this contribution, we present an approach to mitigate the computational costs of simulation-based LSP process optimization. The approach is based on sampling the optimization parameter space by computing several simulations while varying the optimized parameters. Next, the precomputed solutions are used to construct a reduced order model (ROM) usable in optimization. ROM in question leverages proper orthogonal decomposition (POD) and artificial neural networks (ANNs). Compared to the original full order model (FOM), ROM evaluation is by orders of magnitude faster. Furthermore, the loss of information between FOM and ROM can be controlled during the ROM construction.*

Keywords: laser shock peening, modeling, simulation, finite volume method, OpenFOAM

1. Introduction

Laser shock peening (LSP) is a process of hardening a material surface by means of a high power density laser. The specific variant of the process that is of interest in this contribution is depicted in Fig. 1a. For a detailed description of the process, the reader is referred to (Scius-Bertrand et al., 2020) or our previous work (Isoz et al., 2023, 2024). LSP has been simulated since 1990s; see (Braisted and Brockman, 1999) and the standard approach is: (i) to use a separate model for conversion of the laser energy to plasma and, finally, to plasma-generated pressure; and to prescribe the laser-component interaction through a pressure boundary condition loading the material for $\mathcal{O}(10^{-7})$ s; (ii) to simulate separately the propagation of the shock wave, which plasticizes the material and has temporal scales of $\mathcal{O}(10^{-6})$ s, and the relaxation of the material in-between pulses, which has temporal scales of $\mathcal{O}(10^{-1})$ s. The standard simulation approach is shown in Fig. 1b.

Due to the requirements on the mesh resolution and time step, simulations of LSP with multiple laser shots and real component geometries are computationally intensive. Typical industrially relevant meshes have $\mathcal{O}(10^{7})$ degrees of freedom while the time step during the explicit solution of shockwave propagation is $\mathcal{O}(10^{-9})$ s. Simultaneously, the industry is interested in optimization of the LSP process parameters in

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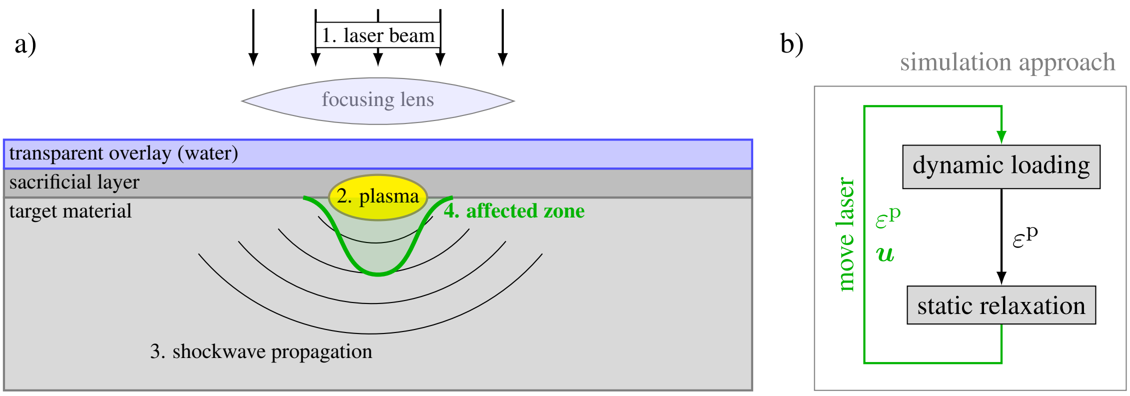

Fig. 1: Fundamentals of the (a) laser shock peening process; (b) approach to simulation of switching between dynamic plastic wave propagation and pseudo-static relaxation while sharing data on displacements ($\boldsymbol{u}$) and plastic strains (ε^{p}).

order to fully leverage the fact that LSP is a high-precision surface treatment where the accuracy of spot-positioning on the component surface can be $\mathcal{O}(10^{-1})$ mm with the typical spot size of $\mathcal{O}(10^{0})$ mm.

A potential approach to alleviate the computational costs of simulation-based optimization of LSP parameters is to leverage the methods of a posteriori model order reduction (MOR). In a posteriori MOR, the system parameter space is first sampled using the original full order model (FOM). Then, the FOM results and, in some approaches, the FOM structure are used to prepare a reduced order model (ROM). A standard approach is to obtain an orthonormal reduced basis of the FOM results (*system snapshots*), using the proper orthogonal decomposition (POD) (Pearson, 1901), and to use this basis to construct the ROM via Galerkin projection (Volkwein, 2013). The non-linearities in the FOM are then treated, for example, through the discrete empirical interpolation method (DEIM) by Chaturantabut and Sorensen (2010)

Constructing ROM for the LSP simulation by the combination of POD, Galerkin projection, and DEIM is problematic due to the standard simulation approach, see Fig. 1b. Specifically, the simulation of each LSP shot comprises two separate steps, and the combined system cannot be easily projected using the POD basis. In this contribution, we circumvent the projection by leveraging a purely data-driven approach to the ROM construction in which the projected system is replaced by artificial neural networks (ANNs). The MOR approach is similar to the works (Hesthaven and Ubbiali, 2018; Kovárnová et al., 2025), it combines POD with ANNs and hereafter, it will be abbreviated as PODIANN, that is, Proper Orthogonal Decomposition with Interpolation via Artificial Neural Networks. The PODIANN framework is applied in an exemplary multi-objective optimization of LSP in which the spot size and spots overlap are varied in order to obtain the optimal trade-off between the uniformity and amplitude of residual stresses in the treated component.

2. Full order model and optimization problem

The details of the laser shock peening simulation using the finite volume method are given in (Isoz et al., 2023, 2024). Here, we consider an illustrative problem of treating a part represented by a two-dimensional rectangular domain. The simulation is performed under the assumption of small and plane strain. The simulation domain as well as the used finite volume mesh are shown in Fig. 2a. In Fig. 2b, we show a typical simulation result after LSP using shots of the radius $r = 0.65\,\mathrm{mm}$ with the overlap $o = 0.9$ of the spot radius.

For the problem studied, the part was considered to be made of perfectly plastic steel with Young modulus $Y = 210\,\mathrm{GPa}$, Poisson ratio $\nu = 0.3$, density $\rho = 7800\,\mathrm{kg\,m^{-3}}$, and yield strength $\sigma_{\mathrm{y}} = 600\,\mathrm{MPa}$. The laser was assumed to correspond to the Litron laser used in the HiLASE Centre of the Institute of Physics of the CAS. The laser energy is $E = 3\,\mathrm{J}$, the beam is circular and top-hat in both space and time with duration of approximately $17\,\mathrm{ns}$. For the conversion of the laser illumination intensity to the temporal evolution of the pressure loading of the component surface, the model proposed for top-hat lasers in (Scius-Bertrand et al., 2020) was used. For the spatial pressure distribution, we applied a model similar to the one given in (Sun et al., 2022; Isoz et al., 2024) but modified for plane strain conditions.

The goal of the optimization performed was to find an optimal trade-off between the uniformity and amplitude of residual stresses in the region of interest (RoI) depicted in Fig. 2b. The amplitude was quantified through $\mathrm{mean}_{\mathrm{RoI}}\,(\sigma_{\mathrm{eq}})$ and the uniformity through $\mathrm{stdev}_{\mathrm{RoI}}\,(\sigma_{\mathrm{eq}})$. The varied parameters were the radius

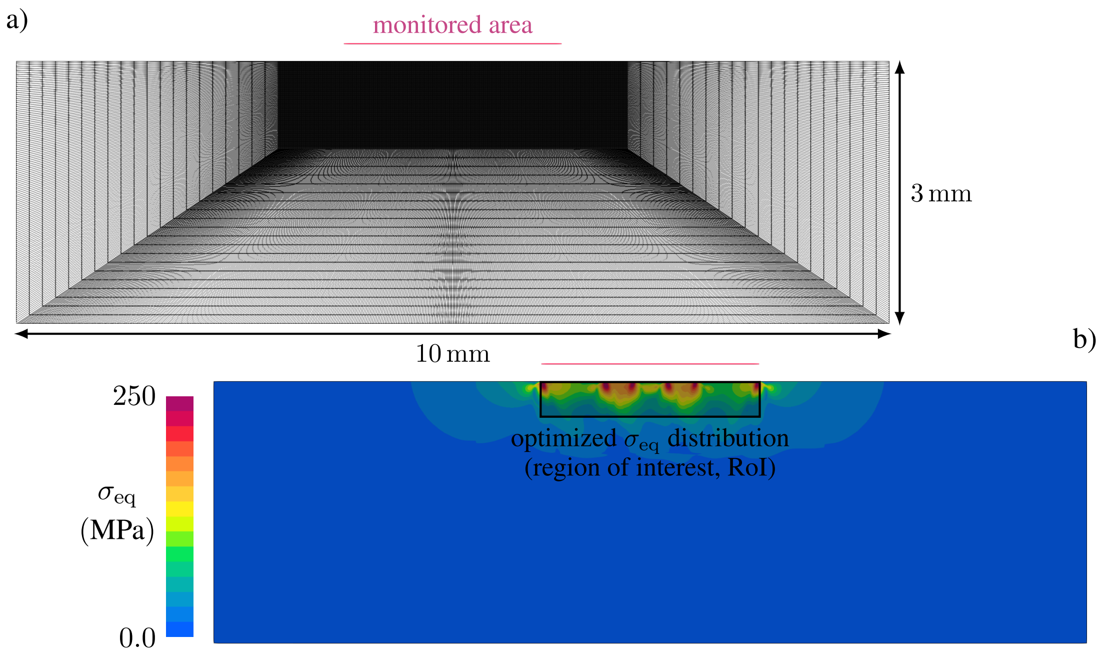

Fig. 2: Illustrative problem, (a) geometry and mesh, (b) typical distribution of residual stress under the monitored area with spot radius of $r = 0.65\,\mathrm{mm}$ *and overlap* $o = 0.9$.

of the LSP shot $r \in \langle 0.50, 0.75\rangle$ mm and the overlap of the individual shots $o \in \langle 0.0, 1.0\rangle \times 100\,\%$ of r. Note that given the fixed laser energy, increasing the spot radius leads to decrease in the laser power density. Furthermore, in all simulations, the surface under the monitored area, see Fig. 2a, always had to be fully treated. Consequently, the number of shots used to treat the component varied with changes of r and o.

3. Reduced order model construction and process optimization

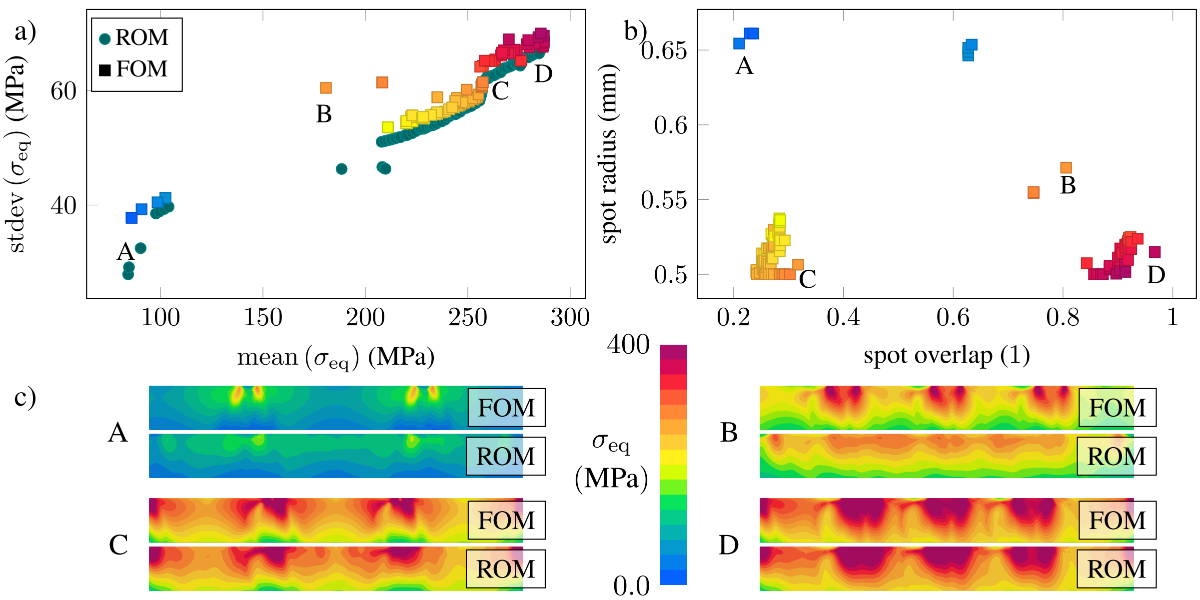

Fig. 3: Results of ROM-based optimization, (a) Pareto-optimal front as predicted by ROM and recomputed by FOM, (b) Pareto-optimal set colored accordingly to FOM in (a), (c) qualitative comparison of typical FOM and ROM results.

The dataset on which the reduced order model is based comprises 231 data points that are linearly distributed across the ranges of considered overlaps (21 points) and spot radii (11 points). The snaphots of σ_{eq} for the tested parameters were combined in a matrix $Y = [\boldsymbol{y}_1, \ldots, \boldsymbol{y}_{231}] \in \mathbb{R}^{m\times 231}$, where $m \approx 90000$ is the spatial resolution of the used FV mesh. From Y, the fluctuations $\boldsymbol{y}_i' = \boldsymbol{y}_i - \mathrm{mean}_{\mathrm{row}}(Y)$ are extracted, with $\mathrm{mean}_{\mathrm{row}}(Y)$ being the row-wise average of the data in Y.

In PODIANN, POD is used to construct a reduced basis of $Y' = [\boldsymbol{y}'_1, \ldots, \boldsymbol{y}'_{231}] = \Psi\, H$, where Ψ are the spatial modes and $H^{\mathrm{T}} = [\boldsymbol{\eta}_1, \ldots, \boldsymbol{\eta}_{231}]$ are parameter-dependent mode amplitudes. The first 14 POD modes are used to represent Y' with the relative reconstruction error in the Frobenius norm of 10^{-2}. Then, a two-layer perceptron ANN with sigmoid transfer function and 30 neurons in each hidden layer is trained to estimate $\boldsymbol{\eta}_i,\ i = 1, \ldots, 14$, for previously unseen parameter values. The reduced order model is used in the NSGA-II algorithm by Deb et al. (2002) to find Pareto-optimal combinations of spot radius and overlap with respect to $\mathrm{mean_{RoI}}\,(\sigma_{\mathrm{eq}})$ (maximization) and $\mathrm{stdev_{RoI}}\,(\sigma_{\mathrm{eq}})$ (minimization).

Pareto optimal set comprising 100 combinations of r and o found using the reduced order model (5000 model evaluations, ≈ 0.6 s/evaluation on a standard laptop) was recomputed in FOM ($\approx$ 100 s/evaluation). The results are given in Fig. 3, including a qualitative comparison between FOM and ROM. Note that ROM consistently predicts lower $\mathrm{stdev_{RoI}}\,(\sigma_{\mathrm{eq}})$ than FOM, which is to be expected since truncating the POD basis corresponds to filtering variance in the source data. Still, apart from a few problematic points, ROM was able to provide an acceptable estimate of the problem Pareto-optimal set.

4. Conclusions

Our in-house developed FVM-based framework for LSP simulations was linked with an a-posteriori approach to reduced order modeling, PODIANN. A reduced order model based on proper orthogonal decomposition and artificial neural networks was used in NSGA-II to find a suitable combination of spot overlap and size to endow the treated component with a residual stress of acceptable magnitude and uniformity. Thanks to a good agreement between the ROM-predicted and FOM-recomputed Pareto-optimal solutions, two promising clusters of parameter settings were identified. Small shots of $r \approx 0.5$ mm with high power density and $o \approx 0.9$ provide high mean magnitudes of residual stress at the cost of inferior uniformity of the stress distribution. On the other hand, shots of similar size but with $o \approx 0.3$ provide $\approx 10\,\%$ lower stress magnitudes but with $\approx 17\,\%$ lower standard deviation of stresses in the optimized zone.

Acknowledgments

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