A model-based framework for monitoring and validation of stochastic processes.

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A major challenge associated with modeling of stochastic processes is the sensitivity of the process to the initial conditions and instability that can develop due to confounding effects during the process. Traditional regression techniques lack the ability to capture details and anomalies occurring in the process, limiting the model's ability to predict instability. Full-physics FEA models create high resolution and accurate snapshots of the state of the system at discrete timesteps but are sensitive to initial conditions and have long runtimes, making them unsuitable for process monitoring.

The proposed framework utilizes machine learning to bridge the gap between high resolution FEA models and basic regression models, allowing users to monitor process effectiveness in real time.

Identification of Basic Physics, Process Defining Distributions

Stochastic processes can be loosely defined as any process where the result is determined by a set of random and distributed variables[3]. These can include mechanical processes (shot peening and milling), chemical processes (corrosion and synthesis), and kinetic processes (agglomeration and sintering). For any stochastic process, there is a set of fundamental physics that causes the process to yield an expected set of results, as well as a critical set of distributed and random variables that cause uncertainty in the results of the process.

Figure 1. Example images of a turbine blade undergoing a shot peening process (via Progressive Surface) and a sample of ball milling media.

Shot peening problem description:

Critical Physics:
- Solid mechanics
  - Elasto-plastic load response
- Contact mechanics
  - Contact formulation
  - Interfacial friction

Random Variables:
- Set of particles impacting part
- Local arrangement of impacts on surface

Distributed Variables:
- Size and shape of particles
- Mass flow rate
- Impact velocity

Finite Element Simulations with Monte Carlo sampling of initial conditions

FEA is a valuable tool for solving non-linear behavior of mechanical and chemical processes, but it's computation time can make it's use impractical for complicated systems[2][4][5]. In order to utilize FEA for simulating a stochastic process, the process needs to be reduced into small, repeatable units, known as representative volume elements(RVE). For shot peening, the RVE can be considered as a small section of the peened part surface, about 25 mm^2 in size. The size of the RVE should be optimized so that there is little stochastic variability between RVE's generated under the same process conditions, while the size remains computationally efficient.

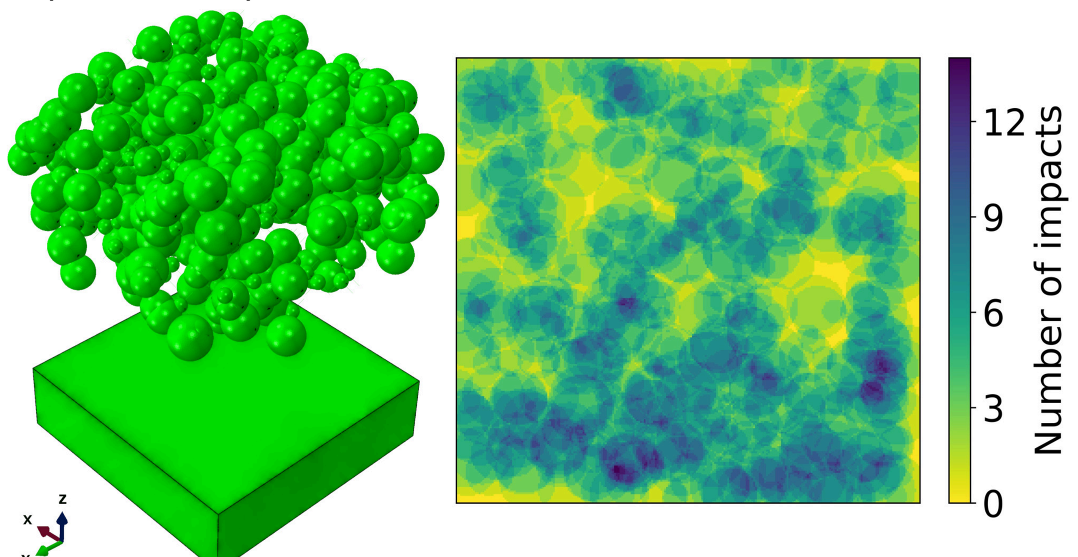


Figure 2. FEA simulation of shot peening with sampling of particle size and shape distributions. Impacts were distributed randomly on the surface of the RVE.

High resolution simulations of RVE's are generated, sampling both the random and distributed process variables. For shot peening, the mass flux of particles contacting the surface during the peening cycle, the impact velocity of the particles, and the size and shape distributions of the particles are systematically sampled as distributed variables. A design of experiments definitive screening approach can be employed, ensuring a representative range of all distributed variables is achieved. The size of the RVE should ensure that the of each simulation results converge to the mean, regardless of the random process variables.

Summary:
- Physics based modeling to provide accurate and high-resolution results.
- Long runtime and resource intensive.

Best for:
- Creating training data for ML models.
- Analyses of potential process instabilities.

Particle Size and Shape Characterization

Media size and shape distributions are critical inputs to the model. **Dynamic Image Analysis** (DIA) provides rapid measurement and presents data in a format that is conducive to sampling[6].

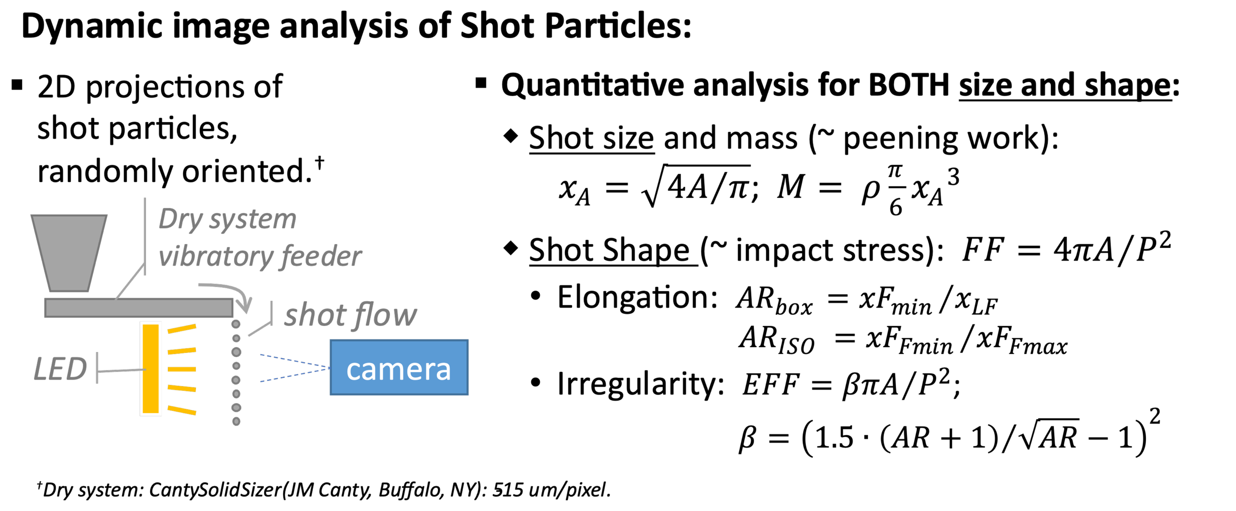


Figure 3. SolidSizer (JM Canty) measures size and shape distributions of particulate media.

Archetypal models translate 2-D projections into number and volume-based distributions used in FEA and ML models[1].

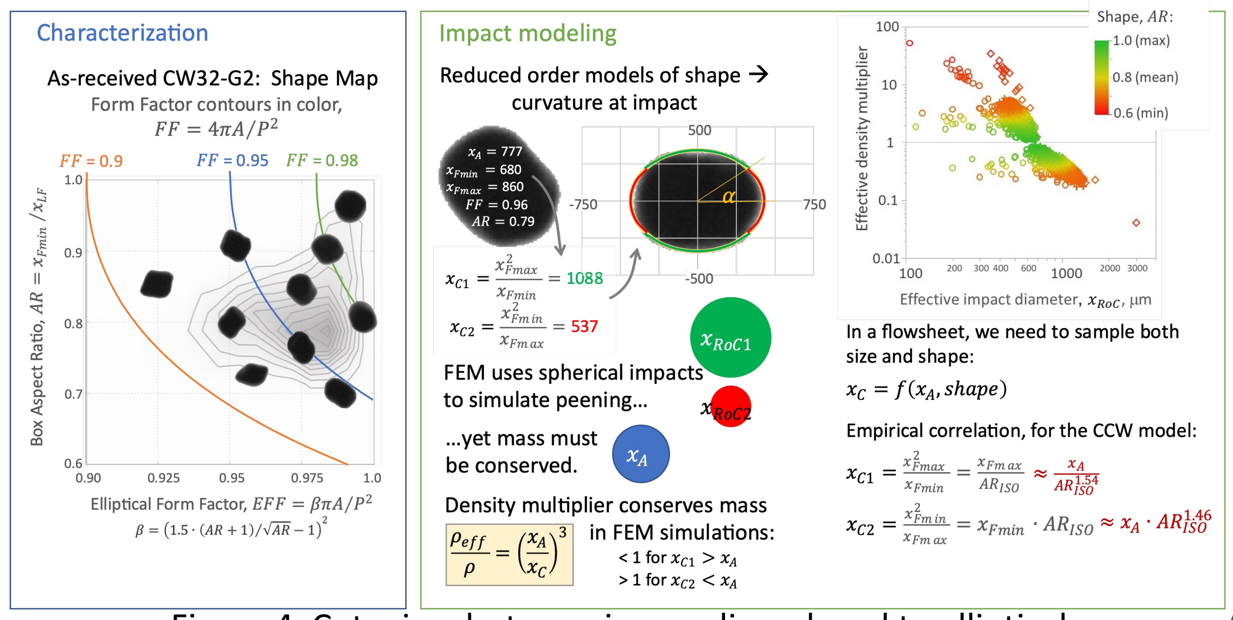
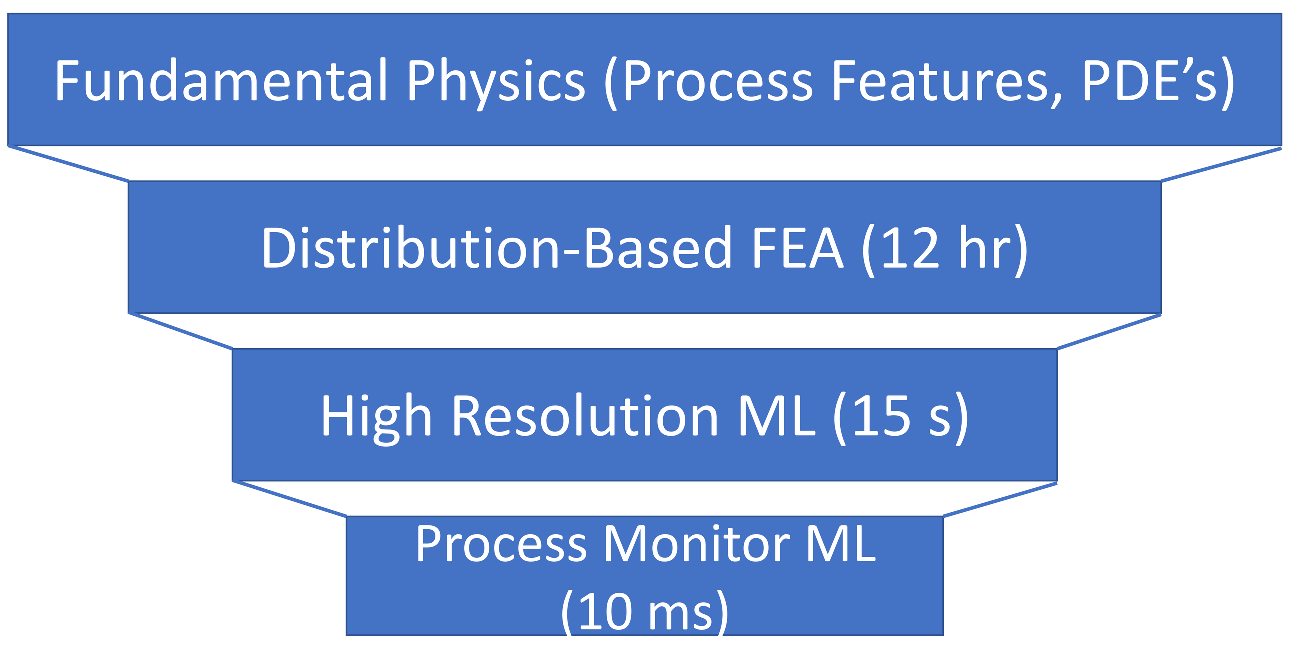


Figure 4. Cut-wire shot peening media reduced to elliptical archetypes having 2 radii of spherical contact per particle with an effective density.



Process Monitoring Machine Learning

High-res machine learning models generate FEA-like data in a fraction of the time. ML models feed statistical models for process monitoring.

A large range of peening process parameters and media distributions were sampled, yielding thousands of combinations assessed by the high-resolution ML model.

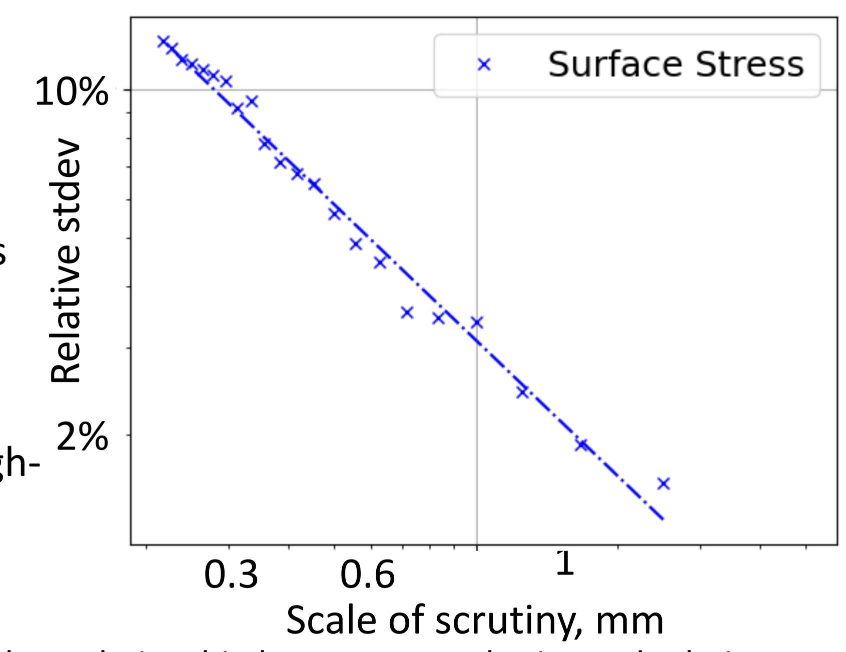


Figure 5. Power law relationship between sample size and relative standard deviation in surface stress for a shot peening simulation.

Summary:
- Statistical models based on scenarios generated from the high-resolution ML model.
- Process monitoring statistics include mean surface stress and confidence interval based on scale of scrutiny.
- Process monitoring and validation.
- Anomaly detection.

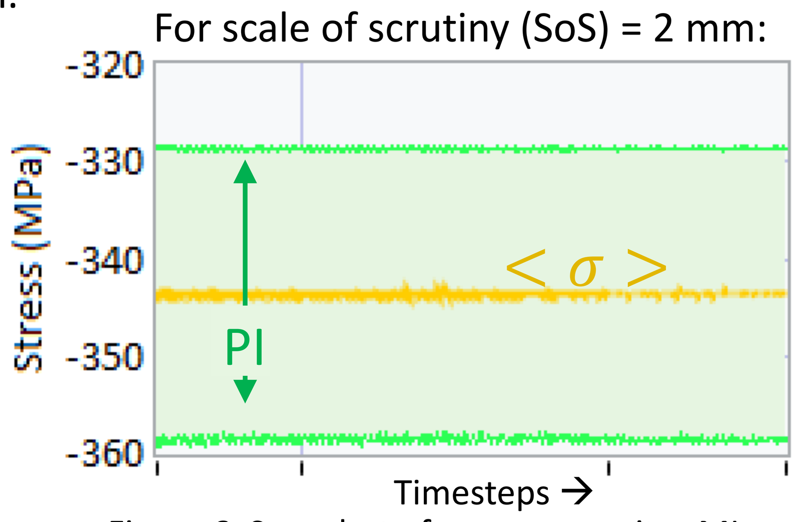


Figure 6. Snapshot of process monitor ML in the flowsheet setting.

High Resolution Machine Learning, Surrogate Models

To fully account for both distributed and stochastic variability in a process, FEA can be too computationally inefficient and complicated to distill into usable information. For training of basic statistics models, the sample size needed far exceeds the number of FEA simulations which is feasible to run on a desktop PC. Instead, the FEA data can be used as training data for a high-resolution machine learning model, with the intention of creating a surrogate for FEA, allowing rapid sampling of distributed and random variables.

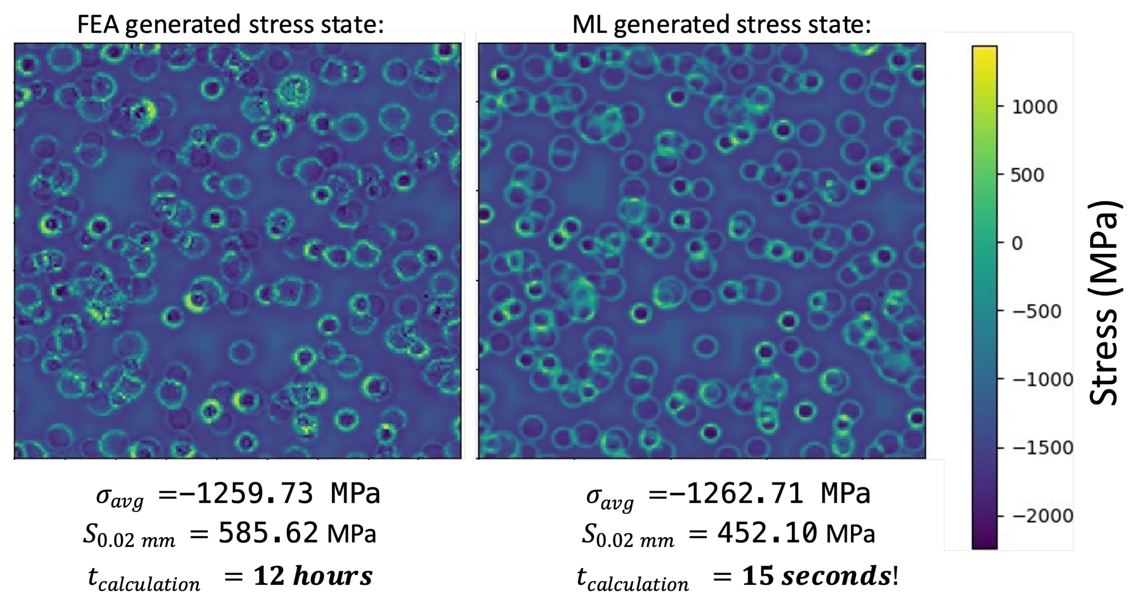


Figure 7. Comparison of FEA to high resolution ML results for the same set of initial conditions.

To create high-resolution model:
- Project the FEA models into images, showing the initial and final conditions of the system.
- Identify the **isoeffect region**, defined as the region affected by each event, divide the image of the system into all possible isoeffect regions.
- Utilize a **Convolutional Neural Network** to predict the final conditions of each iso-effect region.

Summary:
- High resolution spatial stress distribution.
- Based on convolutional neural network platform, sampling of initial conditions.

Best for:
- Analyses of stochastic variability in process outcome.
- Detailed analyses of stress state within FEA training range.

Flowsheet Implementation w/Recycle Loop

Linking all three levels of models together is a flow sheet platform, employing modal-based tracking of media distributions, along with random sampling of the stochastic components of the process.

The flowsheet framework provides users with an unambiguous way to ensure process quality and detect phenomena that can have a significant impact on process outcomes. All 3 levels of models can be integrated into the flowsheet, meaning any result can be passed through all of the models.

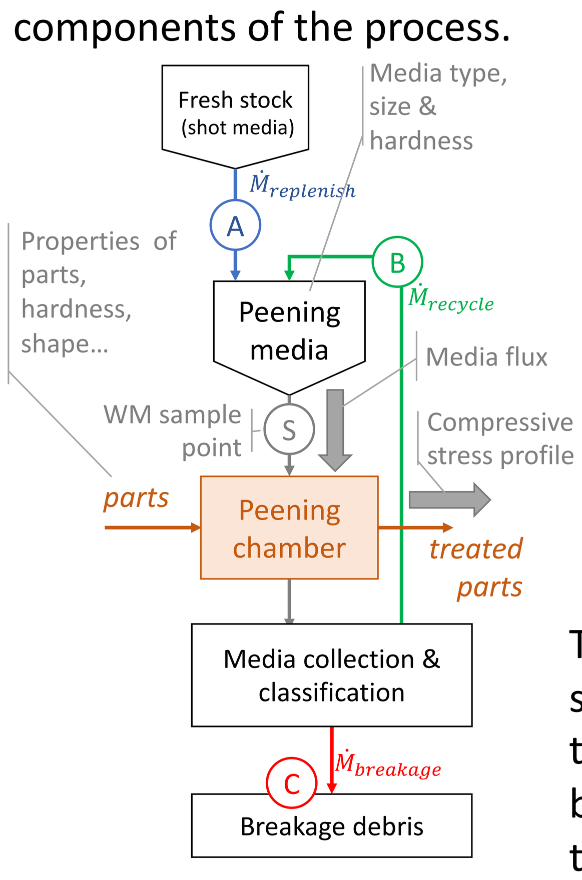


Figure 8. Basic framework of the flowsheet model for shot peening applications.

This allows the framework to be self-validating and allows the user the ability to identify anomalies by linking statistical models with the higher-resolution ML model, and investigate the fundamental reasons for the behavior through FEA modeling.

In shot peening, tracking the breakage and recycle of media is handled by a sum of modes, with characteristic parameters that determine the rate of media shape change based on number of cycles. A periodic recharge of as manufactured media replaces the worn media as it leaves the system.

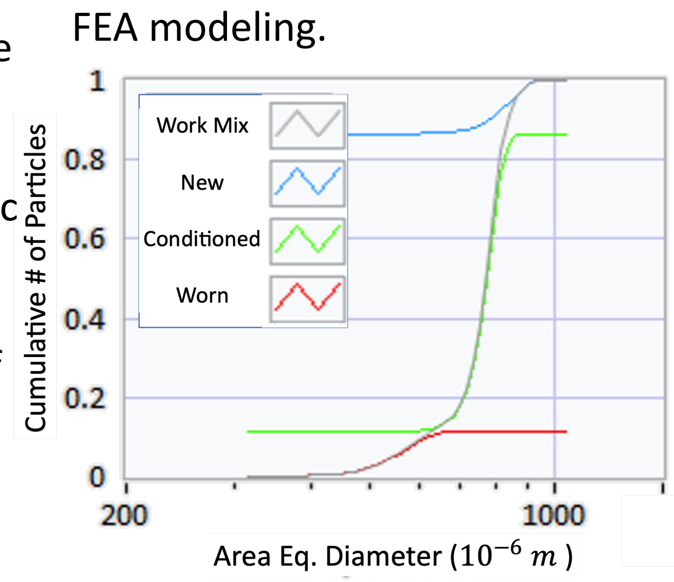


Figure 9. The media population is defined as a mix of as-manufactured, conditioned, and worn particles.

References

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