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DEFORM® News

Training:

- December 10-13, 2019: DEFORM training will be conducted at the SFTC office in Columbus, Ohio.
- February 11-14, 2020: DEFORM training will be conducted at the SFTC office in Columbus, Ohio.
- April 14-17, 2020: DEFORM training will be conducted at the SFTC office in Columbus, Ohio.

Design Environment for FORMing

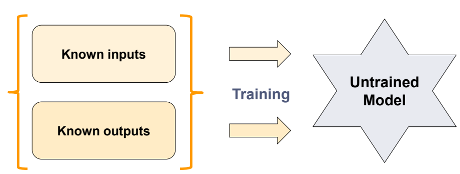
Data Analytics

Big data, deep learning, cloud computing, artificial intelligence and Industry 4.0 are commonly heard terms in the business world. While they may seem like buzz-words, they instead represent the future of technology. These innovations are beginning to have an impact in many industries, with manufacturing environments being no exception.

Industry 4.0 is a name for what is defined as the fourth industrial revolution. This is said to take the computers and automation introduced during the third industrial revolution and "enhance it with smart and autonomous systems fueled by data and machine learning".[1]

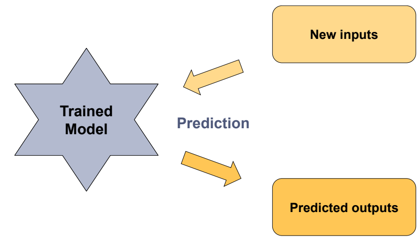
Data analytics and machine learning are key to the revolution. Data analytics is a process of examining, comparing and modeling data sets and their relationships. Various machine learning techniques are available as modeling methods. Learning algorithms build predictive relationships that allow insight into complex non-linear behavior.[2]

Unlike finite element modeling (FEM), data analytics tools perform their analysis by plotting data, computing statistics and building models from existing information. They find relationships between known inputs and known outputs by "training" a machine learning model to identify hidden patterns and trends, as illustrated below.



Once a trained model is established, new input values can be fed into the model and the associated outputs will be predicted. This is illustrated in the following graphic. Quite simply, analytics figure out how or why something happened and uses that understanding to find what might happen in alternate scenarios.

This state-of-the-art technology is now offered in DEFORM through the new



Data Analytics Module. Existing modules support advanced tools including design of experiments (DOE), optimization, integrated computational materials engineering (ICME) and probabalistic modeling.

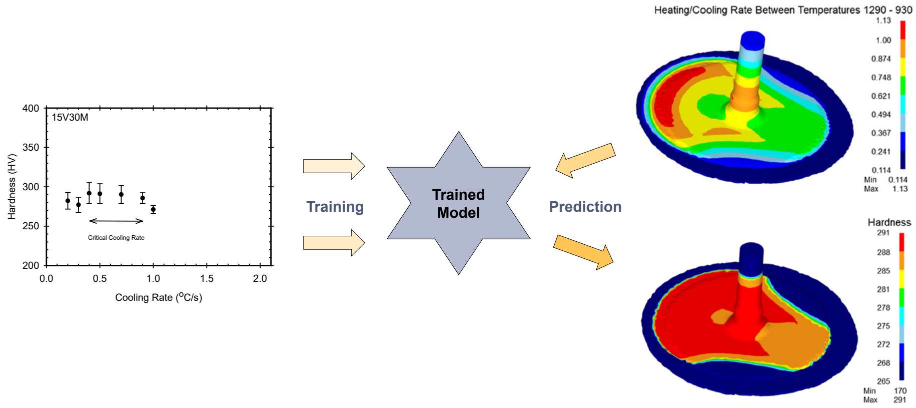
The new data analytics tools are broadly applicable, accepting data sets from many sources. Experimental data could come from coordinate measurement machines (CMMs), load cells, strain gages, thermocouples or other instruments. Numerical results may be imported from DEFORM or other software. Heuristic rules, based on human experience, or emperical formulas can also be integrated.

The tools are also flexible, serving many purposes. Sensitivity analysis determines which process inputs have the greatest influence on the outputs. FEM simulations can be directly compared to experimental data. It might be useful for developing a surrogate model that predicts process response when a FEM simulation is too computationally intensive. FEM or postprocessing could also be extended by coupling them to trained models.

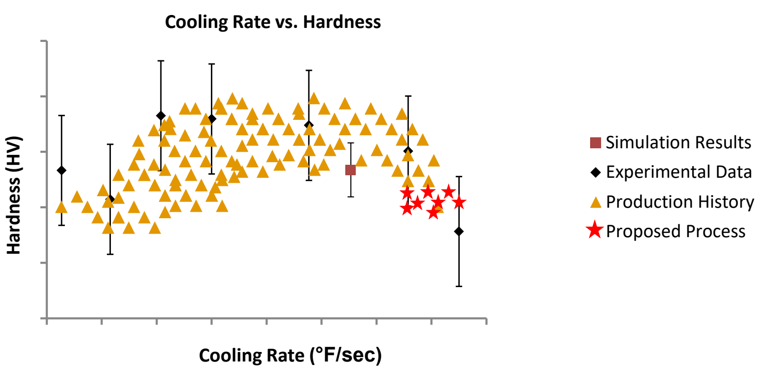
All data analytics projects follow the same workflow. A user imports data, organizes it, establishes a goal and chooses a model type. Available models include regression, Gaussian, neural network, equation fitting or linear interpolation. Studies support more than one model type, expressions combining multiple models and use of one model as input to another.

Relationships are to be validated once a training or predictive run is completed. Predicted results must be compared to the measured output data during training validation. Graphical and error-estimating statistical tools simplify this process. A trained model has been established once a suitable match is found. The trained model is then ready for predicting new outputs for the new input data sets.

Data analytics is demonstrated, below, using the microalloyed steel cooling rate study* described in the Summer 2017 DEFORM News. In the study, laboratory tests determined how a controlled cooling rate impacted the hardness of microalloyed steel billets. This set of known inputs and outputs (left) was used to train a data analytics model characterizing the relationship (center). A DEFORM-3D simulation result, specifically the cooling rate of a production forging (upper right), was then fed into the trained model as a new input. The trained model output a prediction for the final hardness of the forging (lower right).



Taking this example a step further, one might add production data into the known data set (below). Machine learning tools generally train more effectively as the data size grows.



A second data analytics example developed a surrogate model to predict axial load, torque and spread in shape rolling. 50 DOE simulations were first run to create a process map. Eight design variables were evaluated, involving 3 billet shape, 3 roll shape and 2 process parameters. Input and output variables from the DOE study were fed to a data analytics project as the known data. Statistical tools within the data analytics environment identified which inputs had the most influence on load, torque and spread.

A training model was then created to relate the original input variables to the "known" DOE output variables. Load, torque and spread were subsequently predicted for 10 new input scenarios. The predicted torque was evaluated against the reference torque from the prior DOE simulations. Good agreement (0-9% error) was found between the torque predicted by data analytics and the torque provided by the baseline DOE simulations.

This example illustrates how data analytics can be used as a design system. Simulation, experimental or production results may be utilized to characterize a process. A trained model could then predict response to other scenarios. This would benefit users with quick feedback on new design iterations, without more simulations or physical testing.

The Data Analytics Module was introduced with DEFORM V12.0. It offers an opportunity for users to integrate data analytics directly within the DEFORM environment. The module is available to users of the DEFORM Premier system. Other users are invited to contact their local DEFORM distributor for more information.

[1] Marr, Bernard. "What is Industry 4.0? Here's A Super Easy Explanation For Anyone." Forbes.com, Sept. 2018.
[2] Lee, Timothy. "How neural networks work–and why they've become big business." Arstechnica.com, Dec. 2019.

Releases:

DEFORM V12.0 Service Pack 1 (V12.0.1) was released in December. It contains verified bug fixes and system enhancements. Select changes include:

- V12 Linux support
- Main menu usability
- Forming Express MO handling
- Solver performance
- Running job status
- Object display defaults
- 2D DXF ellipse entities
- Multi-object scheduled remeshing
- Coating mesh data
- ALE mesh generation
- DOE advanced thermal BCC
- Contact generation speed
- Spinning roll positioning
- Matched cogging die positioning
- Shape rolling twist prevention
- Ring rolling MO setup
- Material unit notations
- BCC unit notations
- Language translations
- Extrusion lab documentation
- Material Suite lab documentation
- License Manager
- Service Control

The complete list of improvements is provided in the V12.0.1 Release Notes. Release notes are included with the software installation and are also available on the DEFORM User Area.

**The microalloyed steel cooling rate study was courtesy of Colorado School of Mines, Jernberg Forge (MPG) and the Forging Industry Educational and Research Foundation (FIERF).*

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