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MACHINE LEARNING-BASED SURROGATE MODEL IN CENTRIFUGAL PUMP DESIGN

SPE-GCS: AI Accelerated Physics Based Modelling and its Role in Energy Industry

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3DEXPERIENCE



Gulf Coast Section

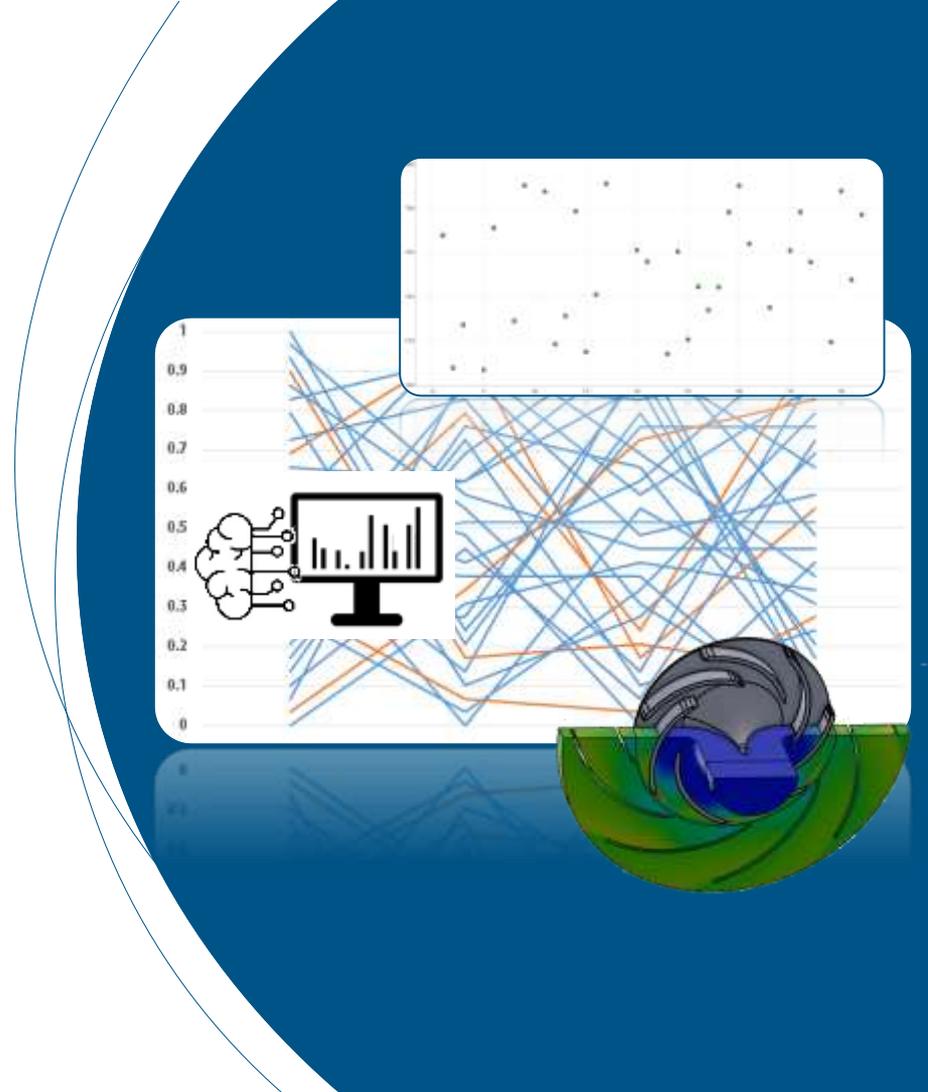


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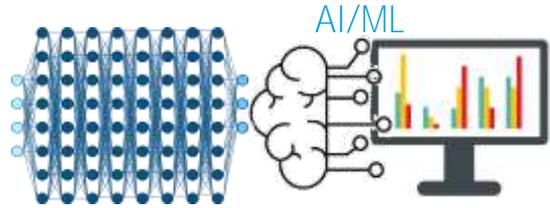
Introduction

AI/ML in SIMULIA Fluids– Overview

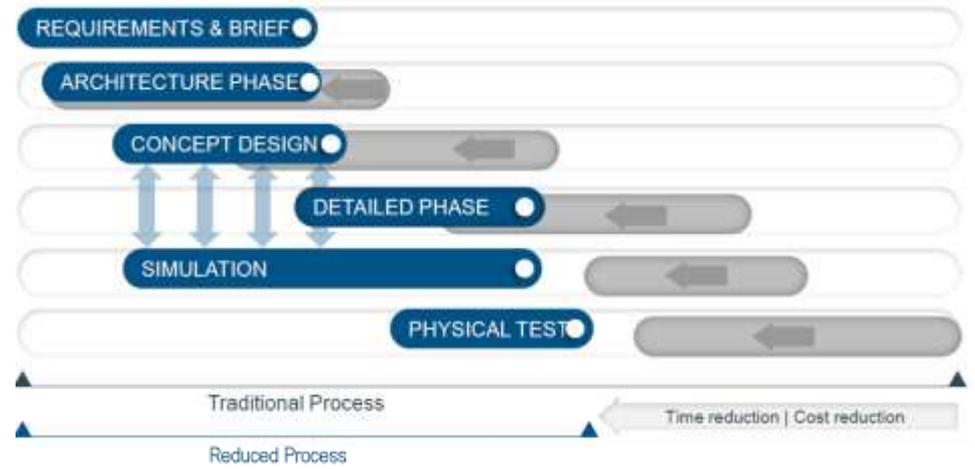
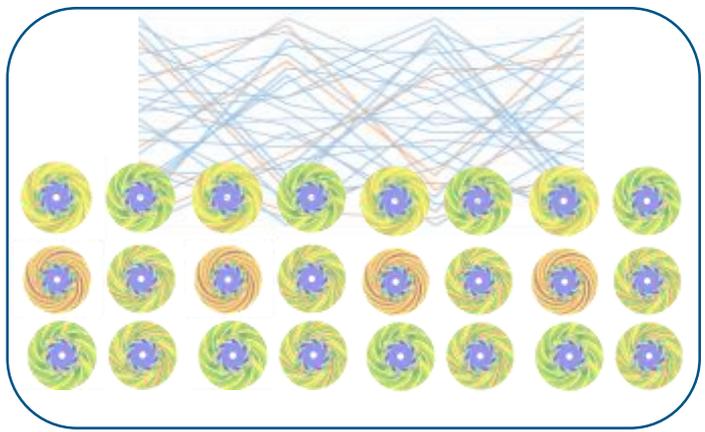
AI/ML in SIMULIA Fluids - Results

Conclusions & Next Steps

BENEFITS OF SOLUTION



Deep Neural Network:
AI/ML uses existing data to
accelerate early stage designs
predictions in a wider design space



Left shifting of project execution

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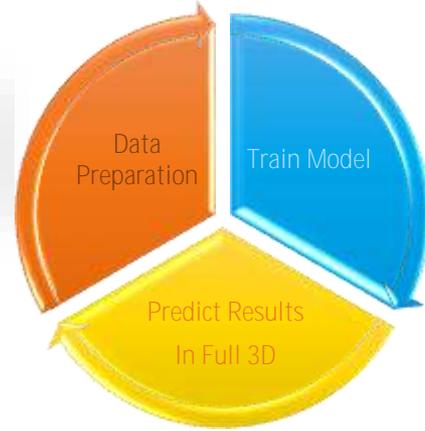
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MACHINE LEARNING FOR 3D DESIGN EXPLORATION

Parametrized models: Geometry, BCs
Run a DOE

Data set preparation from DOE



Train Model Accuracy & Loss

Data Set

Quasi-interactive design explorations – Predictions in the matter of minutes

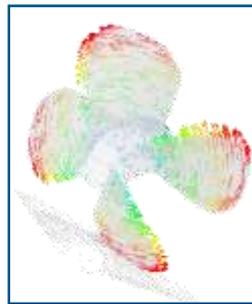
Input Parameters

vane_inlet_angle	<input type="range"/>	68.79deg
vane_outlet_angle	<input type="range"/>	70.52deg
vane_thickness	<input type="range"/>	6.62mm
vane_outlet_dia	<input type="range"/>	698.28mm

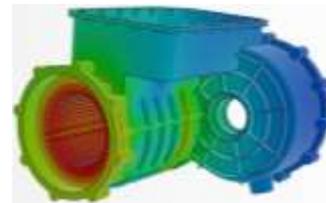
Prediction Output

3DEXPERIENCE[®] CFD | KEY VALUES

- ▶ Designer-centric user experience
 - ▷ CAD & PLM-embedded CFD
 - ▷ Guided User Interface
 - ▷ Automatic fluid volume extraction
 - ▷ One-click simulation model update with design changes
- ▶ Advanced design exploration
 - ▷ Process automation for trade-off studies
 - ▷ Multi-objective design space optimization
 - ▷ Analytics driven decision support
- ▶ Validated for accuracy and efficiency
 - ▷ RANS based steady-state and long transient simulations
 - ▷ Native conjugate heat transfer
 - ▷ Laminar and turbulent flow with intelligent near-wall treatment
 - ▷ Robust hex-dominant body-fitted mesh with boundary layer
- ▶ Unified multiscale multi-physical environment
 - ▷ Capture multidisciplinary requirements (FSI, 3D CFD +1D)



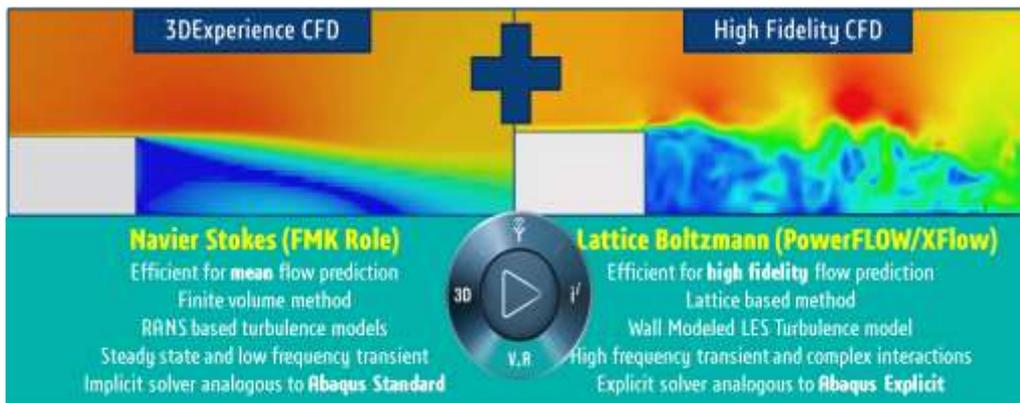
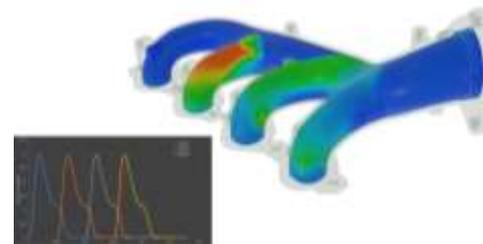
MRF or Sliding Mesh



Transient simulations

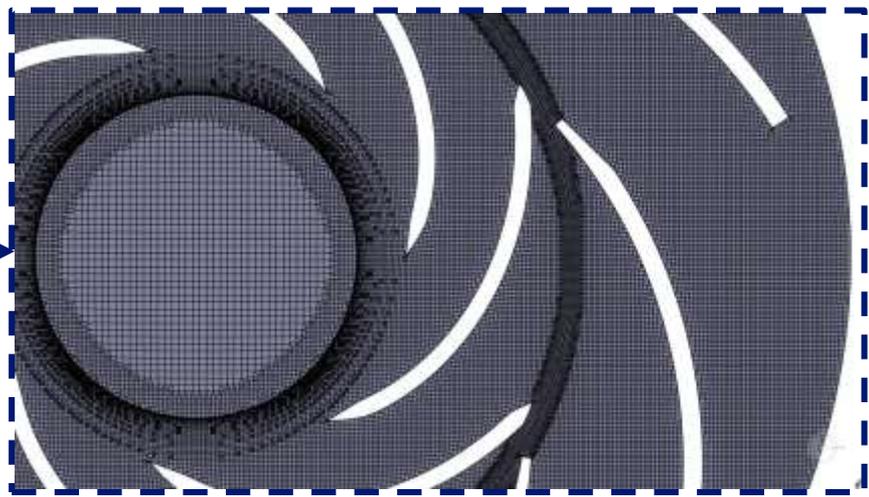
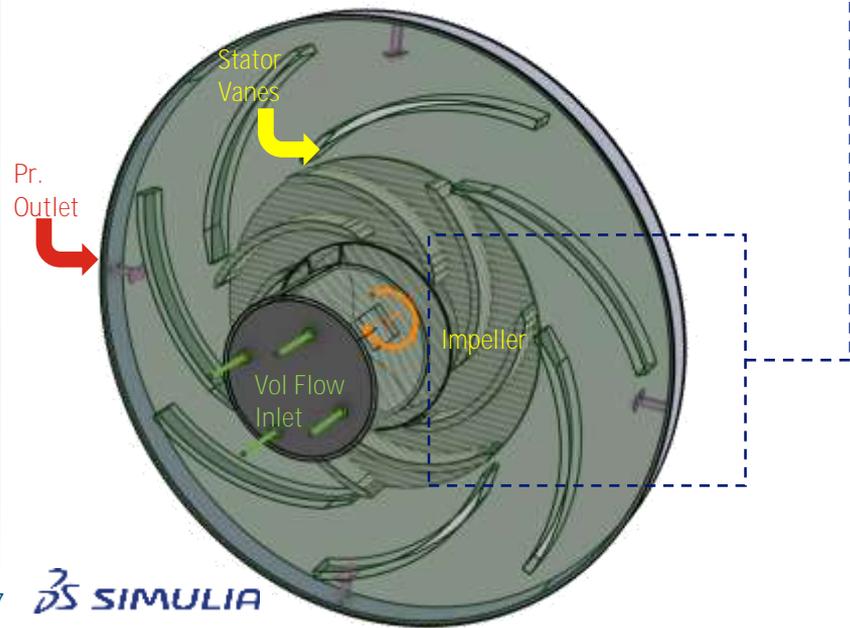


Incompressible Flow



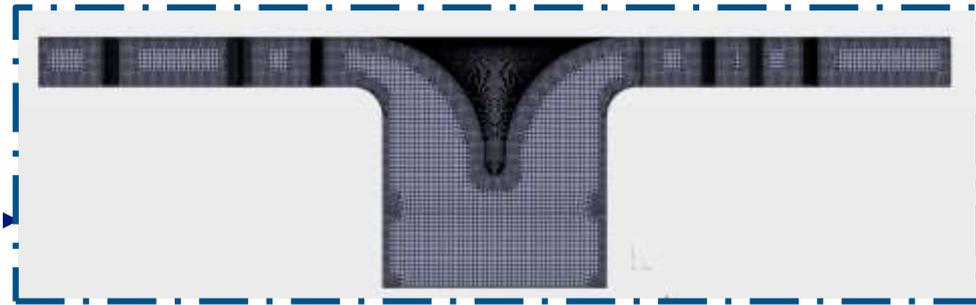
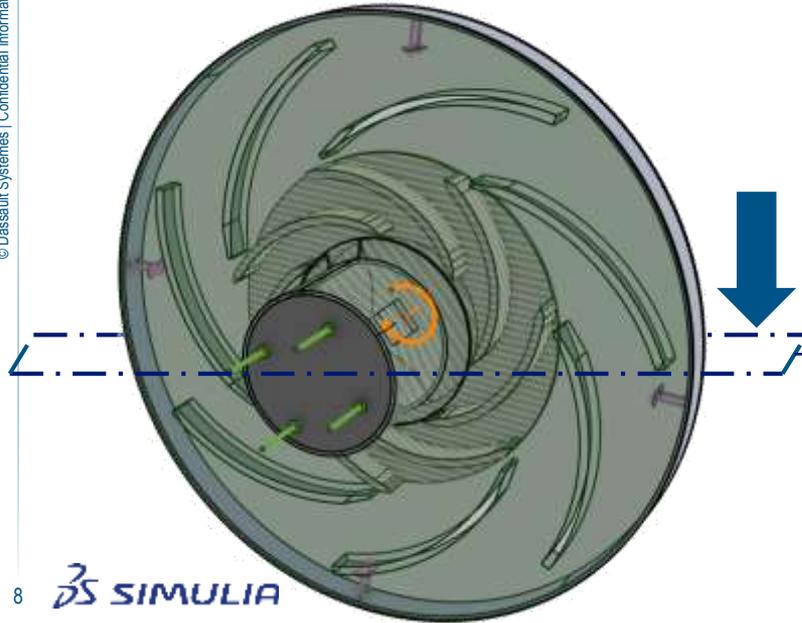
CFD TAC PUMP | BASELINE MODEL

- Vol Flow Inlet = $0.3\text{m}^3/\text{s}$ | Impeller RPM = 2000 | Atmos Outlet
- Steady-state MRF, SST-kw
- KPI: Total Head Rise [Pa] across the system
- Hex mesh grid used as input (~3.5M elements for full domain)



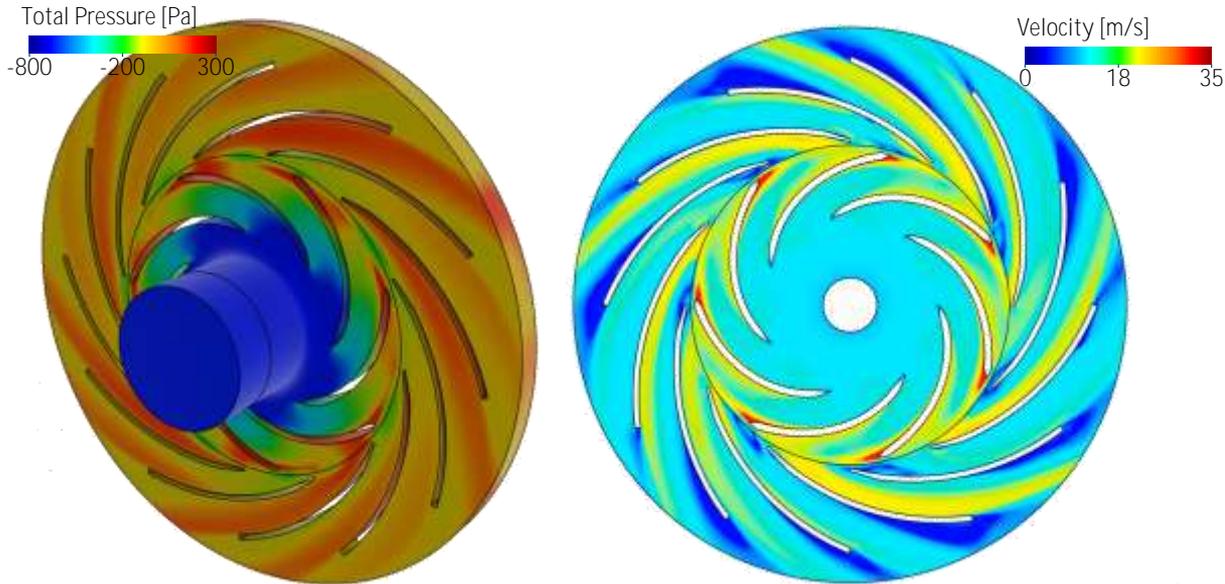
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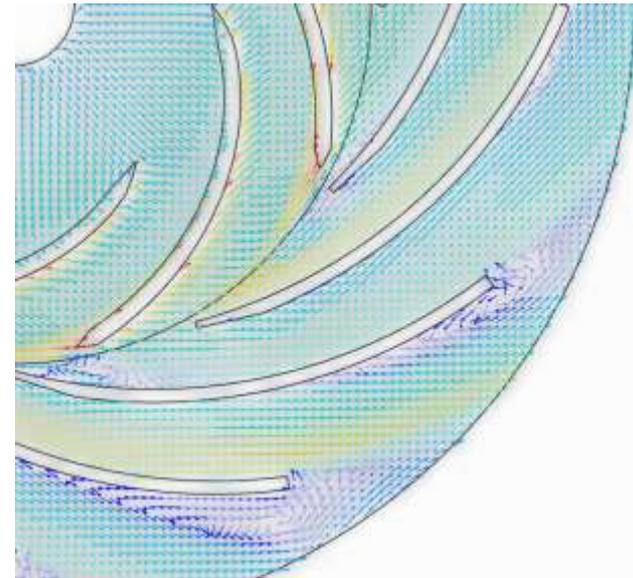


ERCOFTAC PUMP | BASELINE MODEL

- Within 7% of value from Ubaldi, et al.
- Total gauge pressure and velocity plots



Total Pressure, mass Flow avged [Pa]		CPUh
CFD	Ubaldi Exp **	
809.8	757	16

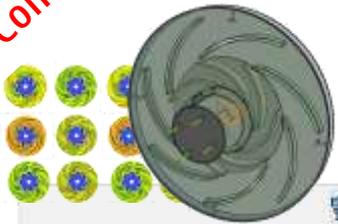


** Ubaldi, Marina, Pietro Zunino, Giovanna Barigozzi, and Andrea Cattanel. "An experimental investigation of stator induced unsteadiness on centrifugal impeller outflow." In *Turbo Expo Power for Land, Sea, and Air*, vol. 78835, p. V001T01A002. American Society of Mechanical Engineers, 1994

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FLOW

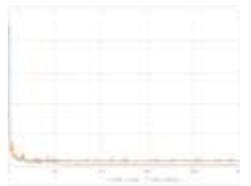


Inputs:
• CFD Parametric DOE Results



Machine Learning Training

Order of hours



If Model is not already trained

1



If Model is already trained



2

Machine Learning Inference

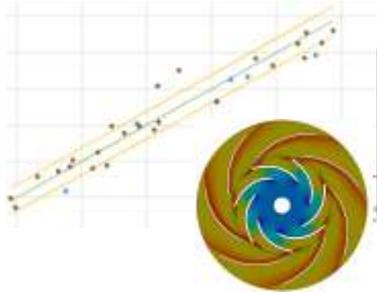
3



Post Processing

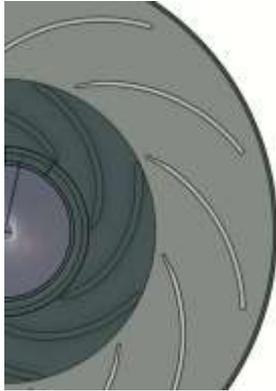
Order of mins

Outputs:
• Predicted 3D Fluid Field (Velocity, Pressure, etc.)
• Predicted 1D Metrics (Pressure, X-Force, etc.)



FTAC PUMP | DOE

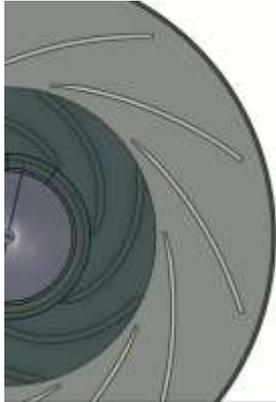
Vane Inlet Angle →
[Range = 25°]



Vane Thickness →
[Range = 6mm]



Vane Outlet Angle →
[Range = 25°]



Chord Length →
[Range = 50mm]



- FMK DOE containing 42 simulations, 4 parameters
 - Adaptive DOE for the initial design spread
- 36 Training set, 6 held-out set [3 test + 3 validation]

Run#	Vane Inlet Angle	Vane Outlet Angle	Vane Outlet Dia	Vane Thickness
37	0.5	0.11	0.47	0.8
38	0.55	0.52	0.01	0.02
39	0.01	0.46	0.07	0.5
40	0.55	0.62	0.74	0.87
41	0.24	0.72	0.68	0.67
42	0.68	0.26	0.2	0.33

■ Test ■ Validation

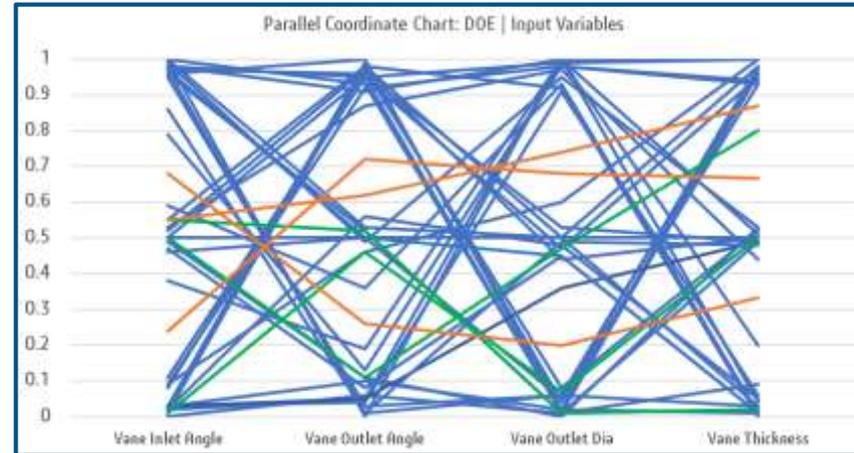


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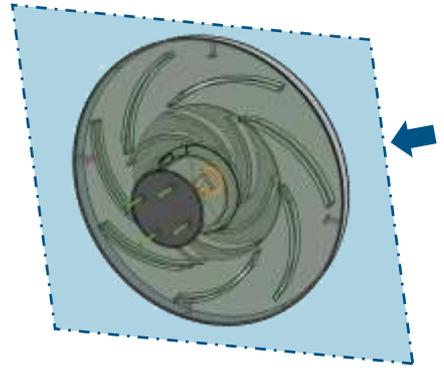
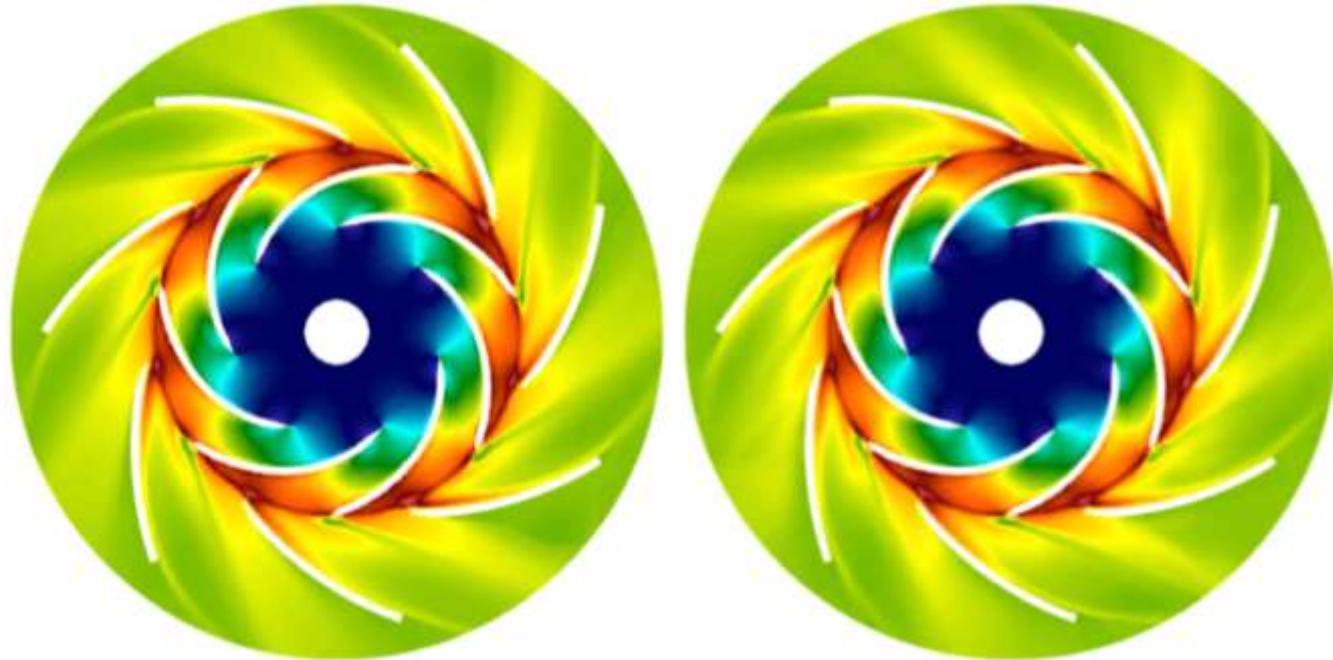
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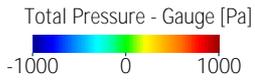
JFTAC PUMP | 3D SLICE PREDICTIONS



Center-aligned slice of total pressure around the blades and vanes show good correlation

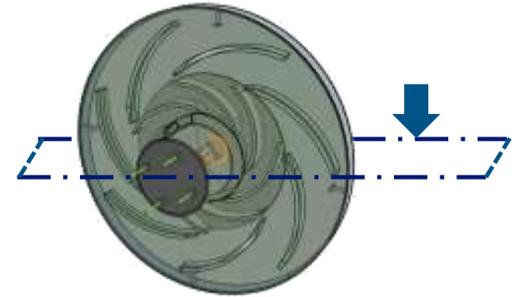
CFD

Prediction



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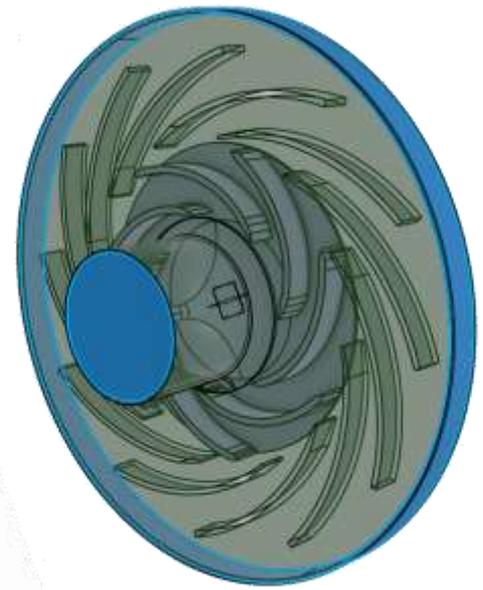
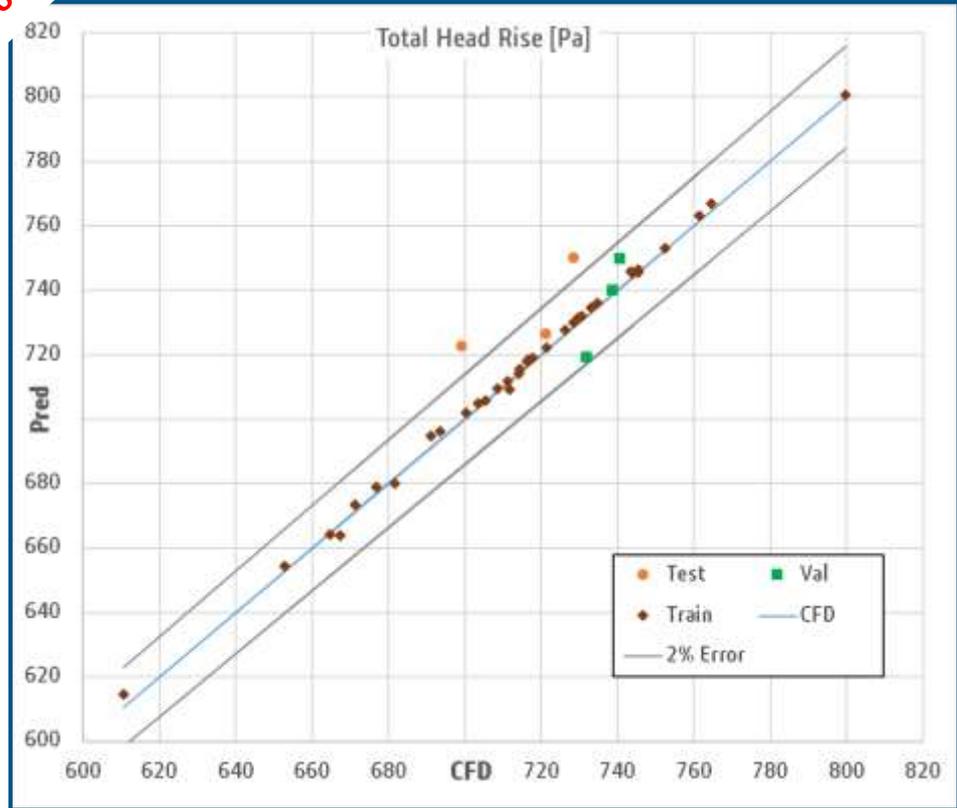
ERCOFTAC PUMP | 3D SLICE PREDICTIONS



Top-view slice of total pressure around the blades and vanes show good correlation



JFTAC PUMP | 3D PREDICTIONS



- Head rise is the difference between 3D integration of inlet and outlet total pressure
- Overall average prediction error is around 1.72%

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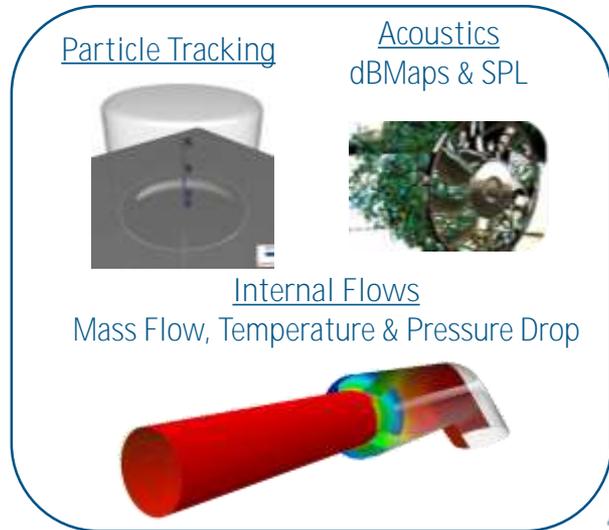
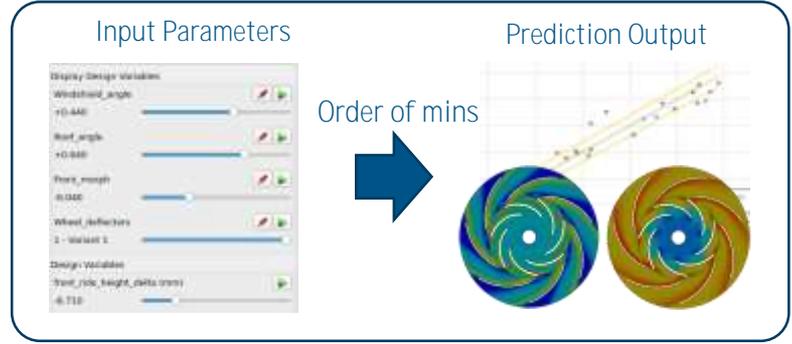
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CONCLUSIONS

- Quality of data is crucial for any ML program
 - SIMULIA offers best-in-class multi-scale and multi-physics portfolio options
- AI/ML can be used successfully with parameterized DOEs built on 3DEXperience CFD
 - Average total head rise prediction error under 1.72%
 - 3D field data is available for every predicted run in a matter of minutes
- Detailed 3D field prediction – Fluid and Surface data
- Reduced hardware requirements – Single GPU sufficient
- Expanding across other fluids applications



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