Machine Learning in Reservoir Production Simulation and Forecast

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Scaling Up and Modeling for Transport and Flow in Porous Media
Dubrovnik, Croatia, 13-16 October 2008
Topics and Goals

• Goals
  – Look at one of topmost levels of model upscaling – dependencies between solution functionals
  – Consider Machine Learning (ML) as possible relevant technology for these levels

• Topics covered
  – Basic problem formulations in ML context
  – Illustrative applications and benefits
To the top of upscaling hierarchy

- Can we upscale original problem of reservoir simulation to the level of functional dependence between observed outputs (e.g. production rates) and controlled inputs (e.g. wells regimes)?

- Is this the only way to do this from original equations?
  - Possibly, alternatives exist: functional and probabilistic dependencies can be simulated by Machine Learning algorithms (neural networks and others)
- PE are the best for direct problems
- PE give useful hints to ML
  - Critical scale factors
  - Conservation laws
  - Constrains
  - Feasibility tests
- ML algorithms are naturally utilize observations, and suitable both for direct and inverse problems
- ML feedbacks to PE
  - Factors influence
  - Optimal factor values

OBSERVATIONS
PHYSICS EQUATIONS
MACHINE LEARNING
Models for what?

• Modelling for synthetic description of many simulator runs and experimental observations
  – “What-if” tools
  – inverse problems
• Modelling for prediction
  – Prolongation of system trajectory in time
  – Future responses to changing controls
• Machine Learning can serve for both
Formulations of ML tasks

- Requested application problem is described in terms of input variables (controlled and uncontrolled) and outputs. Later directly represent variables to be estimated.
- Datasets are collected from simulations and/or observations in the form of pairs of input-output vectors.
- Machine Learning algorithm provides the IO dependence.
  - Functional view – provide approximation of unknown function
  - Probabilistic view – estimate most probable response to a given input (whole probability distribution is preferable)
Types of ML tasks

• Classification problem
  – Output variable(s) represents two or more descriptive alternatives (classes). Current input vector belongs to one of them.

• Regression problem and conditional probability estimation
  – Output(s) is typically real-valued.

• Other (less frequent) problems
  – Clustering (unsupervised, no predefined classes and class labels
  – Reinforcement learning (rewards or punishments are given instead of known output values.
Classification example

• Problem: Hydraulic fracturing is one of successful methods of production intensification. Fracturing efficiency for the particular well is quite uncertain and strongly depends on many factors (used as inputs):
  – Proppant parameters, pumping rate, perforation, watercut, surround media structure, well “history”, etc.

• Approach: consider classification of wells into two classes (“high” and “low” expected efficiency).

• Solution: neural classifier trained on known examples of previous fractures can predict the outcome.
  – Candidate wells are ordered so that most perspective wells for future fracturing planning are identified
Results: 30 wells of 100

Multiple efficiency is over 90%

Sorted by actual output, 30 best forecasted are in green.
Regression example

- Forecast of future scenario of well production (product and watering) from the production history and areal pumping.
- Regression model uses embedded delayed time series as inputs and estimates both expectation and variance of future production.
- Model can be used in control applications and field planning
Quality of 1-year forecast

Matched history

NARX prediction
Machine Learning tools

- Neural Networks
- Probabilistic and clustering trees
- SVM
- Kohonen maps
- GA and other optimization

Example: Cascade Neural Network
Gaussian likelihood optimization with CG

Inputs, [1;b]
Growing cascade
Hidden neurons
Outputs R
Conclusions and benefits

- Machine Learning methods can fruitfully enforce mathematical modelling at topmost level of upscaling.
- Trained models can serve as surrogates for optimization tasks and inverse formulations.
- Both simulated and observed data can be aggregated in one predictive model.
- Broad area of applications in energy industry.

• Thank You!