Probabilistic Assessment of Tight-Gas Sands Using a Data-Driven Modeling Approach*

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Abstract

Tight-gas sand reservoirs are considered to be one of the major unconventional resources. Due to the strong heterogeneity, very low permeability and advanced well designs with multiple hydraulic fractures; performance forecasting, characterization and optimum exploitation of these resources become challenging with conventional modeling approaches. In this study, it is aimed to develop data-driven predictive models for tight-gas sands and use them for probabilistic assessment of these resources. Data-driven models are based on artificial neural networks that can complement the physics-driven modeling approach, namely numerical flow-simulation models.

Two different classes of data-driven models are trained and validated by using data from a numerical reservoir model for tight-gas sand reservoirs: (1) a forward model to predict the horizontal-well performance, once the initial conditions, operational parameters, reservoir/hydraulic-fracture characteristics are provided, and (2) an inverse model to estimate reservoir/hydraulic-fracture characteristics once the initial conditions, operational parameters, observed horizontal-well performance characteristics are provided. The forward model is validated with blind cases by estimating the 10-year horizontal-well performance (i.e., cumulative gas recovery) with an average error of 3.7%. While the development of the inverse model was more challenging due to the inverse nature of the problem, reservoir and hydraulic-fracture characteristics are estimated with an average error below 20%, reducing the uncertainty associated with these parameters significantly. A graphical-user-interface application is developed that offers an opportunity to use the developed tools in a practical manner by visualizing estimated performance for a given reservoir or obtaining estimates of certain reservoir and hydraulic-fracture parameters, within a fraction of a second. Practicality of these models is also demonstrated with a case study for the Williams Fork Formation by assessing the performance of various well designs and by incorporating known uncertainties through Monte Carlo simulation. P10, P50 and P90 estimates of the horizontal-well performance and reservoir/hydraulic-fracture characteristics are quickly obtained within acceptable accuracy levels.

Selected References

Al-Anazi, A., Babadagli, T., 2010, Automatic fracture density update using smart well data and artificial neural networks: Comp & Geosc, v. 36/3, p. 335-347, doi:10.1016/j.cageo.2009.08.005.

Al-Mousa, T., 2014, Multi-lateral well design advisory system; an inverse-looking solution: Abu Dhabi International Petroleum Exhibition and Conference Proceedings, No. SPE-171685-MS, 10-13 November, Abu Dhabi, UAE,. doi:10.2118/171685-MS.

Alizadeh, B., S. Najjari, and A. Kadkhodaie-Ilkhch, 2012, Arti cial neural network modelling and cluster analysis for organic facies and burial history estimation using well log data: A case study of the south pars gas field, Persian Gulf, Iran: Comp & Geosc, v. 45, p. 261-269, doi:10.1016/j.cageo.2011.11.024.

Amirian, E., J. Leung, S. Zanon, and P. Dzurman, 2013, Data-driven modeling approach for recovery performance prediction in sagd operations: SPE Heavy Oil Conference Proceedings, No. SPE-165557-MS, 11-13 June. Calgary, Alberta,. doi:10.2118/165557-MS.

Archie, G., 1950, Introduction to petrophysics of reservoir rocks: AAPG Bull, v. 34/5, p. 943-961.

Arps, J., 1945, Analysis of decline curves: Trans AIME, v. 160/1, p. 228-247.

Artun, E., 2016, Characterizing interwell connectivity in waterflooded reservoirs using data-driven and reduced-physics models: A comparative study: Neural Comput & Applic. doi:10.1007/s00521-015-2152-0.

Artun, E., T. Ertekin, R. Watson, and M. Al-Wadhahi, 2011, Development of universal proxy models for screening and optimization of cyclic pressure pulsing in naturally fractured reservoirs: J N Gas Sci Eng, v. 3/6. 667-686, doi:10.1016/j.jngse.2011.07.016.

Artun, E., T. Ertekin, R. Watson, B. Miller, 2010, Development and testing of proxy models for screening cyclic pressure pulsing process in a depleted, naturally fractured reservoir: J Pet Sci Eng, v. 73/1, p. 73-85. doi:10.1016/j.petrol.2010.05.009.

Artun, E., T. Ertekin, R. Watson, and B. Miller, 2012, Designing cyclic pressure pulsing in naturally fractured reservoirs using an inverse-looking recurrent neural network: Comp & Geosc, v. 38/1, p. 68-79. doi:10.1016/j.cageo.2011.05.006.

Artun, E., and S. Mohaghegh, 2011, Intelligent seismic inversion workflow for high-resolution reservoir characterization: Comp & Geosc, v. 37/2, p. 143-157. doi:10.1016/j.cageo.2010.05.007.

Ayala, L., and T. Ertekin, 2005, Analysis of gas-cycling performance in gas/condensate reservoirs using neuro-simulation: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-95655-MS, 9-12 October, Dallas, Texas,. doi:10.2118/95655-MS.

Baihly, J., D. Grant, L. Fan, and S. Bodwadkar, 2009, Horizontal wells in tight gas sands - a method for risk management to maximize success: SPE Prod & Oper, v. 24/2, p. 277-292, SPE-110067-PA. doi:10.2118/110067-PA.

Balan, B., S. Mohaghegh, and S. Ameri, 1995, State-of-the-art in permeability determination from well log data: Part 1 - A comparative study, model development: SPE Eastern Regional Meeting Proceedings, No. SPE-30978-MS, 18-20 September, Morgantown, West Virginia,. doi:10.2118/30978-MS.

Britt, L., and M. Smith, 2009, Horizontal well completion, stimulation optimization, and risk mitigation: SPE Eastern Regional Meeting Proceedings, No. SPE-125526-MS, 23-25 September, Charleston, West Virginia. doi:10.2118/125526-MS.

Centilmen, A., T. Ertekin, A.S. Grader, 1999, Applications of neural networks in multiwell field development: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-56433-MS, 3-6 October, Houston, Texas. doi:10.2118/56433-MS.

CMG, 2015, Cmg imex reservoir simulation software, version 2015: Computer Modeling Group, Ltd. Calgary, Alberta.

Cullick, A., D. Johnson, and G. Shi, 2006, Improved and more rapid history matching with a nonlinear proxy and global optimization: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-101933-MS, 24-27 September, San Antonio, Texas. doi:10.2118/101933-MS.

Demiryurek, U., F. Banaei-Kashani, C. Shahabi, and F. Wilkinson, 2008, Neural-network based sensitivity analysis for injector-producer relationship identification: SPE Intelligent Energy Conference and Exhibition Proceedings, No. SPE-112124-MS, 25-27 February, Amsterdam, The Netherlands. doi:10.2118/112124-MS.

Demuth, H., and M. Beale, 2002, Neural Network Toolbox for Use with MATLAB: Mathworks, Inc.

Dong, Z., S. Holditch, D. McVay, and W. Ayers, 2012, Global unconventional gas resource assessment: SPE Econ & Man, v. 4/4, p.222-234. doi:10.2118/148365-PA.

Doraisamy, H., T. Ertekin, and A. Grader, 2000, Field development studies by neuro-simulation: an effective coupling of soft and hard computing protocols: Comp & Geosc, v. 26/8, p. 963-973. doi:10.1016/S0098-3004(00)00032-7.

Ely, J., T. Brown, and S. Reed, 1995, Optimization of hydraulic fracture treatment in the williams fork formation of the mesaverde group: SPE Rocky Mountain Regional/Low-Permeability Reservoirs Symposium Proceedings, No. SPE-29551-MS, 20-22 March, Denver, Colorado. doi:10.2118/29551-MS.

Esmaili, S., and S. Mohaghegh, 2016, Full field reservoir modeling of shale assets using advanced data-driven analytics: Geoscience Frontiers, v. 7/1, p. 11-20. doi:10.1016/j.gsf.2014.12.006.

Gokcesu, U., T. Ertekin, and P. Flemings, 2005, Application of neural networks and genetic algorithms in field development studies: 2nd Kuwait International Petroleum Conference and Exhibition Proceedings, 10-12 December, Kuwait City, Kuwait.

Hagan, M., H. Demuth, M. Beale, and O. De Jess, 2014, Neural Network Design, 2nd Edition, Martin Hagan.

Holditch, S., 2006, Tight gas sands: J Pet Technol, v. 58/6, p. 86-93, doi:10.2118/103356-JPT.

Holditch, S., D. Holcomb, and Z. Rahim, 1993, Using tracers to evaluate propped fracture width: SPE Eastern Regional Meeting Proceedings, No. SPE-26922-MS, 2-4 November, Pittsburgh, Pennsylvania. doi:10.2118/26922-MS.

Hornik, K., M. Stinchcombe, and H. White, 1989, Multilayer feedforward networks are universal approximators: Neural Net, v. 25, p. 359-366.

Ilk, D., J. Rushing, A. Perego, T. Blasingame, 2008, Exponential vs. hyperbolic decline in tight gas sands: Understanding the origin and implications for reserve estimates using arps' decline curves: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-116731-MS, 21-24 September, Denver, Colorado. doi:10.2118/116731-MS.

Jansen, J., R. Brouwer, S. Douma, 2009, Closed loop reservoir management: SPE Reservoir Simulation Symposium Proceedings, No. SPE-119098-MS, 2-4 February, The Woodlands, Texas. doi:10.2118/119098-MS.

Johnson, V., and L. Rogers, 2001, Applying soft computing methods to improve the computational tractability of a subsurface simulation-optimization problem: J Pet Sci Eng, v. 29/3-4, p. 153-175. doi:10.1016/S0920-4105(01)00087-0.

Kalantari-Dhaghi, A., S. Mohaghegh, and S. Esmaili, 2015, Data-driven proxy at hydraulic fracture cluster level: a technique for efficient CO_2-enhanced gas recovery and storage assessment in shale reservoir: J Nat Gas Sci Eng, v. 27/2, p. 515-530. doi:10.1016/j.jngse.2015.06.039.

Law, B., and J. Curtis, 2002, Introduction to unconventional petroleum systems: AAPG Bull, v. 86/11, p. 1851-1852.

MATLAB, 2013, Matlab neural network toolbox, version 2013a: Mathworks, Inc. Natick, Massachusetts.

Medeiros, F., E. Ozkan, and H. Kazemi, 2008, Productivity and drainage area of fractured horizontal wells in tight gas reservoirs: SPE Res Eval & Eng, v. 11/5, p. 902-911, SPE-108110-PA. doi:10.2118/108110-PA.

Metz, M., G. Briceno, Q. Fang, E. Diaz, A. Grader, and J. Dvorkin, 2009, Properties of tight gas sand from digital images: SEG Annual Meeting, No. SEG-2009-2135, 25-30 October, Houston, Texas.

Mohaghegh, S., 2011, Reservoir simulation and modeling based on pattern recognition: SPE Digital Energy Conference and Exhibition Proceedings, No. SPE-143179-MS, 19-21 April, The Woodlands, Texas. doi:10.2118/143179-MS.

Mohaghegh, S., Y. Al-Mehairi, R. Gaskari, M. Maysami, Y. Khazaeni, M. Gashut, A. Al-Hammadi, and S. Kumar, 2014, Data-driven reservoir management of a giant mature oil field in the middle east: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-170660-MS, 27-29 October, Amsterdam, The Netherlands. doi:10.2118/170660-MS.

Mohaghegh, S., A. Modavi, H. Hafez, M. Haajizadeh, M. Kenawy, and S. Guruswamy, 2006, Development of surrogate reservoir models (srm) for fast-track analysis of complex reservoirs: SPE Intelligent Energy Conference and Exhibition Proceedings, No. SPE-99667-MS, 11-13 April, Amsterdam, The Netherlands. doi:10.2118/99667-MS.

Parada, C.H., and T. Ertekin, 2012, A new screening tool for improved oil recovery methods using artificial neural networks: SPE Western Regional Meeting Proceedings, No. SPE-153321-MS, 19-23 March, Bakersfield, California. doi:10.2118/153321-MS.

Patel, A., D. Davis, C. Guthrie, D. Tuk, T. Nguyen, and J. Williams, 2005, Optimizing cyclic steam oil production with genetic algorithms: SPE Western Regional Meeting Proceedings, No. SPE-93906-MS, 30 March - 1 April, Irvine, California. doi:10.2118/93906-MS.

Raeesi, M., A. Moradzadeh, F. Ardejani, and M. Rahimi, 2012, Classification and identification of hydrocarbon reservoir lithofacies and their heterogeneity using seismic attributes, logs data and artificial neural networks: J Pet Sci Eng, v. 82-83, p. 151-165. doi:10.1016/j.petrol.2012.01.012.

Reeves, S., D. Hill, C. Hopkins, M. Conway, R. Tiner, and S. Mohaghegh, 1999a, Restimulation technology for tight gas sand wells: SPE Annual Technical Conference and Exhibition Proceedings, No. SPE-56482-MS, 3-6 October, Houston, Texas. doi:10.2118/56482-MS.

Reeves, S., D. Hill, R. Tiner, P. Bastian, M. Conway, and S. Mohaghegh, 1999b, Restimulation of tight gas sand wells in the rocky mountain region: SPE Rocky Mountain Regional Meeting Proceedings, No. SPE-55627-MS, 15-18 May, Gillette, Wyoming. doi:10.2118/55627-MS.

Silva, P., C. Maschio, and D. Schiozer, 2007, Use of neuro-simulation techniques as proxies to reservoir simulator: Application in production history matching: J Pet Sci Eng, v. 57/3-4, p. 273-280. doi:10.1016/j.petrol.2006.10.012.

Smith, T., C. Sayers, and C. Sondergeld, 2009, Rock properties in low-porosity/low-permeability sandstones: Leading Edge, v. 28, p. 24-59.

Soliman, M., L. East, J. Ansah, and H. Wang, 2008, Testing and design of hydraulic fractures in tight gas formations: SPE Russian Oil & Gas Technical Conference and Exhibition Proceedings, No. SPE-114988-RU, 28-30 October, Moscow, Russia. doi:10.2118/114988-RU.

Solomatine, D., L. See, and R. Abrahart, 2008, Practical Hydroinformatics. v. 68. Springer, Ch. Data-driven modeling: concepts, approaches and experiences, p. 17-30.

Tang, H., W. Meddaugh, and N. Toomey, 2011, Using an artificial-neural-network method to predict carbonate well log facies successfully: SPE Res Eval & Eng, v. 14 /1, p. 35-44, SPE-123988-PA. doi:10.2118/123988-PA.

Timur, A., 1968, An investigation of permeability, porosity, and residual water saturation relationships for sandstone reservoirs: The Log Analyst, v. 9/4, p. 8-17.

Zangl, G., M. Giovannoli, and M. Stundner, 2006, Application of artificial intelligence in gas storage management: SPE Europec/EAGE Annual Conference and Exhibition Proceedings, No. SPE-100133-MS, 12-15 June, Vienna, Austria. doi:10.2118/100133-MS.

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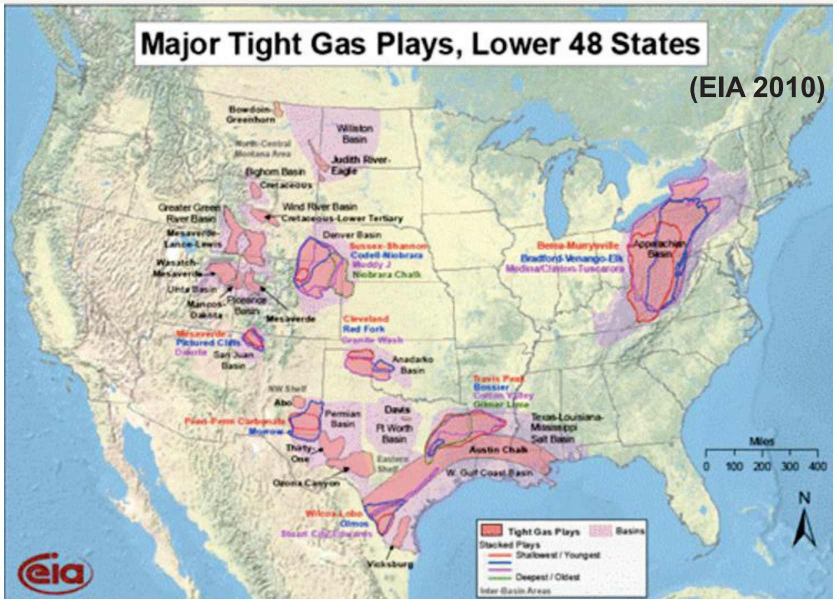
Overview

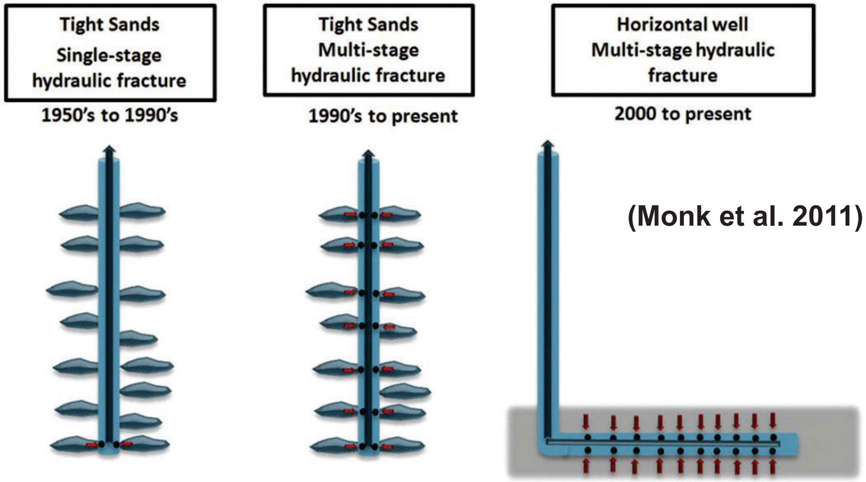
1. Introduction/Motivation
2. Methodology
3. Results & Discussion
4. Conclusions

Introduction/Motivation

Introduction

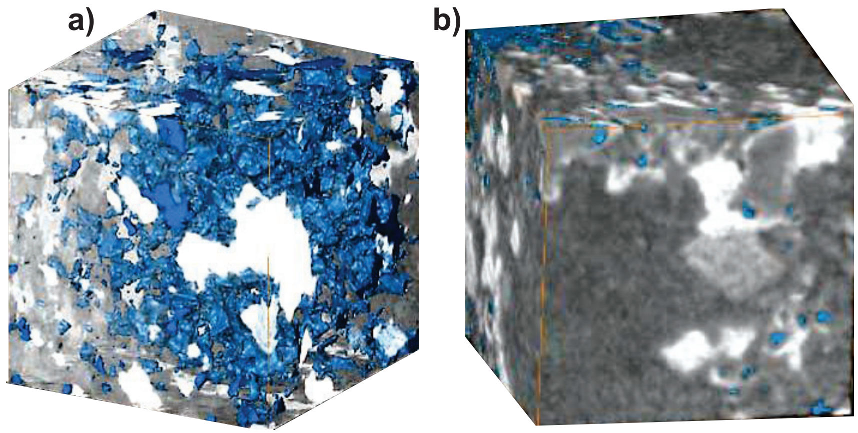
- Tight-gas sands: producible natural gas from reservoirs that have permeability values less than 0.1 md, which usually occurs in sandstone formations
- A major resource with an estimate of the original-gas-in-place of 71,981 TCF worldwide (Dong 2012)
- A recovery design with horizontal wells with multiple hydraulic fractures is necessary





Characterization of Tight-Gas Sands

- Strong heterogeneity → Pores with narrow capillaries → Very low permeability in millidarcy to nanodarcy ranges
- Heterogeneity through out the formation (e.g., Williams Fork)



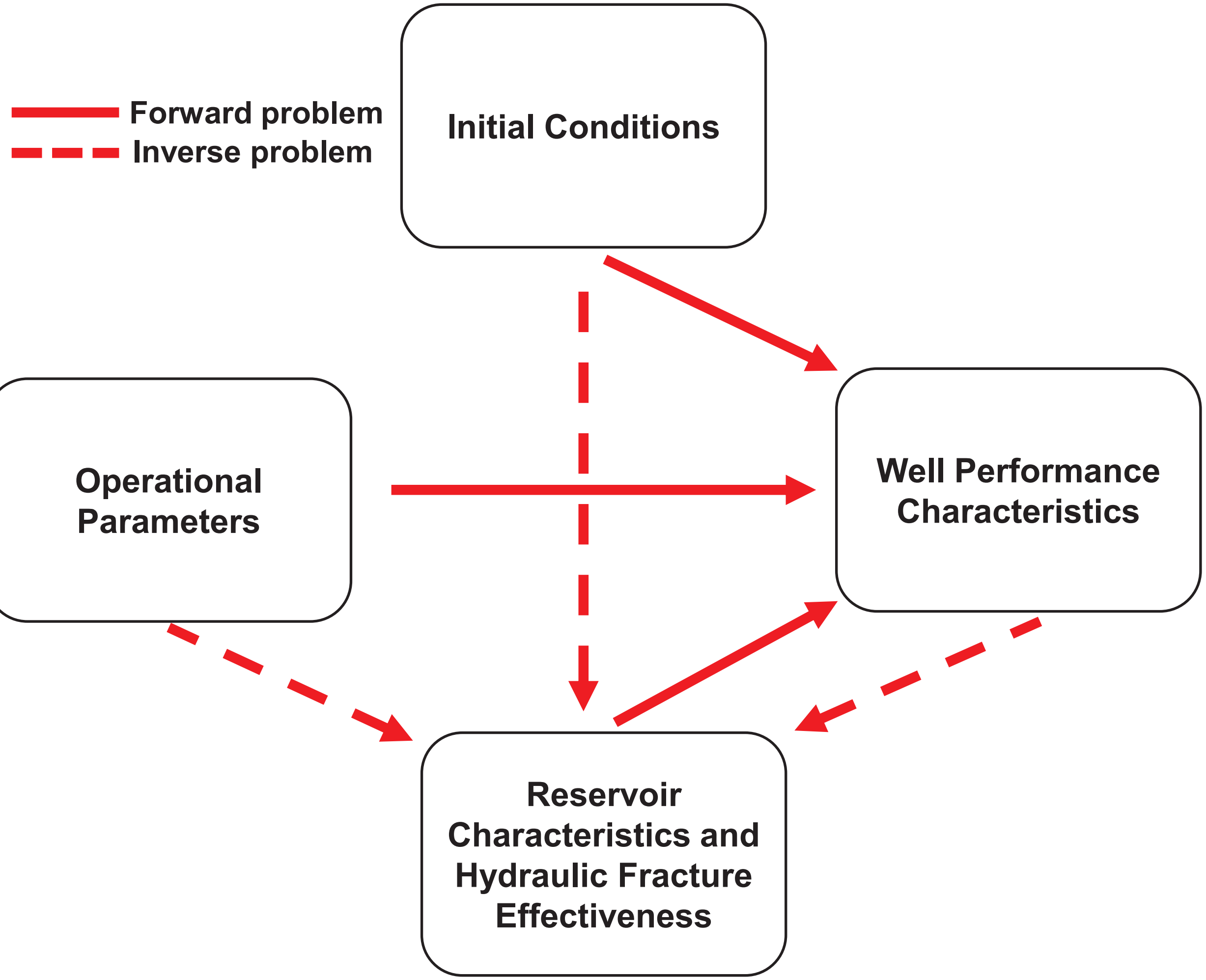
- Challenges in characterization and evaluation of dynamic and static reservoir parameters from well logs, borehole or surface microseismic surveys and core samples (Forsyth et al. 2011, Bahrami et al. 2013, Moore et al. 2016)

Performance Forecasting of Tight-Gas Sands

- Model-building process and quick evaluation of reservoir performance are resource-demanding due to existence of horizontal wells with multiple hydraulic fractures (Abacioglu et al. 2009)
- Advanced numerical models can cause excessive simulation times if not trigger convergence problems or simulation failures
- These challenges become more significant while dealing with uncertainties in parameters: Thousands of simulation runs are needed for a probabilistic assessment

Objectives (1/2): Data-Driven Screening Tools

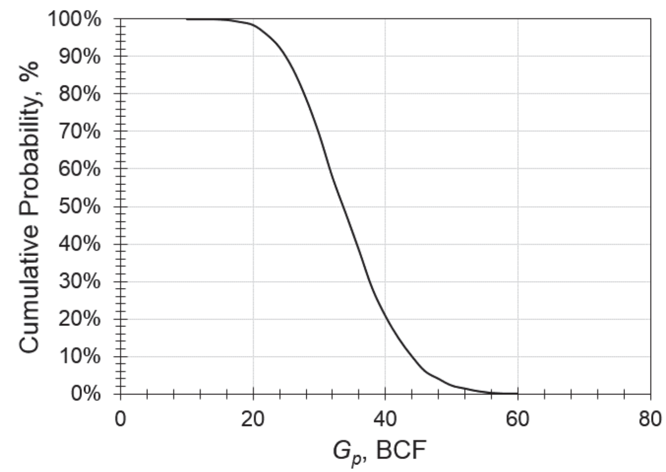
1. A forward-looking performance forecasting tool
2. An inverse-looking reservoir characterization tool



Objectives (2/2): Probabilistic Assessment

- It is aimed to structure an efficient workflow for probabilistic assessment of tight-gas sands:
  - By defining the distribution function and ranges of input parameters, Monte Carlo simulation can be performed
  - After simulating a large number of scenarios, the uncertainty range the output parameters can be quantified

	k, md	***φ***
Minimum	0.05	0.08
Most Likely	0.07	0.11
Maximum	0.1	0.14
Distribution	Triangular	Normal



Methodology

Data-Driven Modeling via Numerical Models

- Construct a representative reservoir model

- Generate a representative set of scenarios

- Run all scenarios, and create a knowledge base with the results

- Train the data-driven model with the knowledge base

- Validate the data-driven model and use it as a predictive tool

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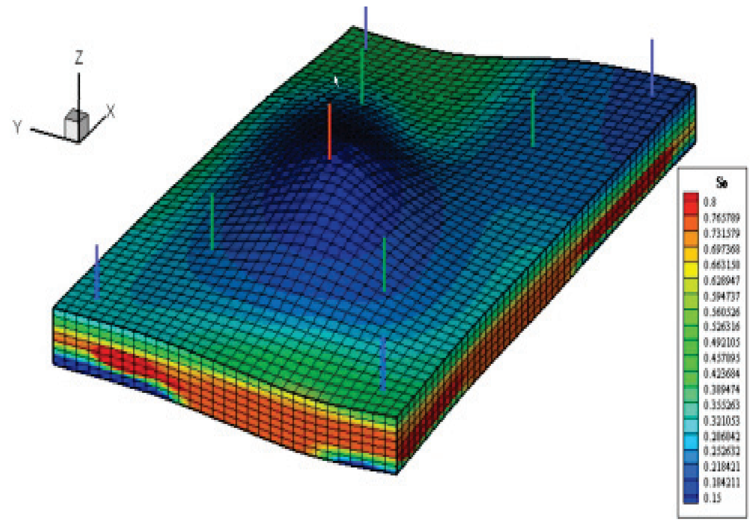

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n	***k, md***	***φ***
1	0.05	0.095
2	0.075	0.013
3	0.04	0.081
4	0.06	0.089
⋮	⋮	⋮
10,000	0.042	0.0125

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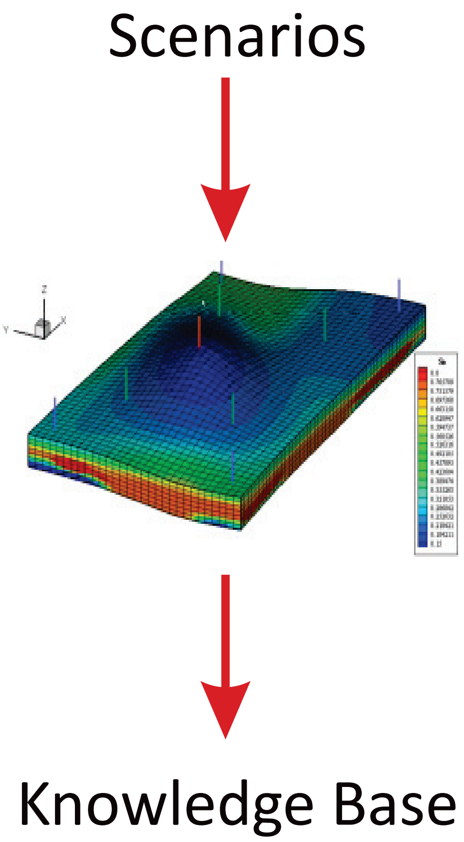

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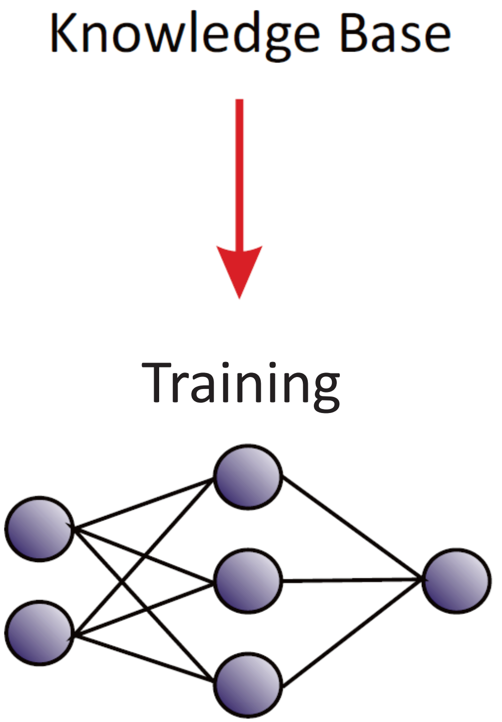

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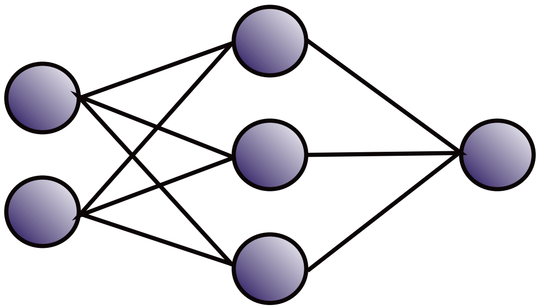

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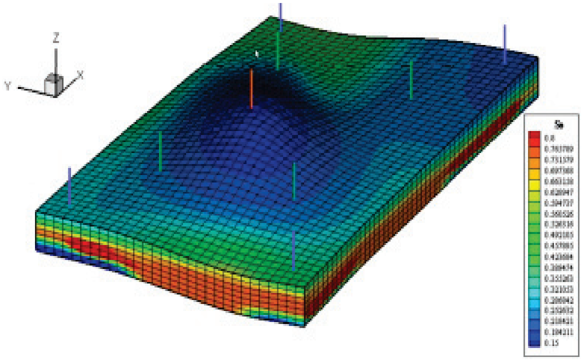
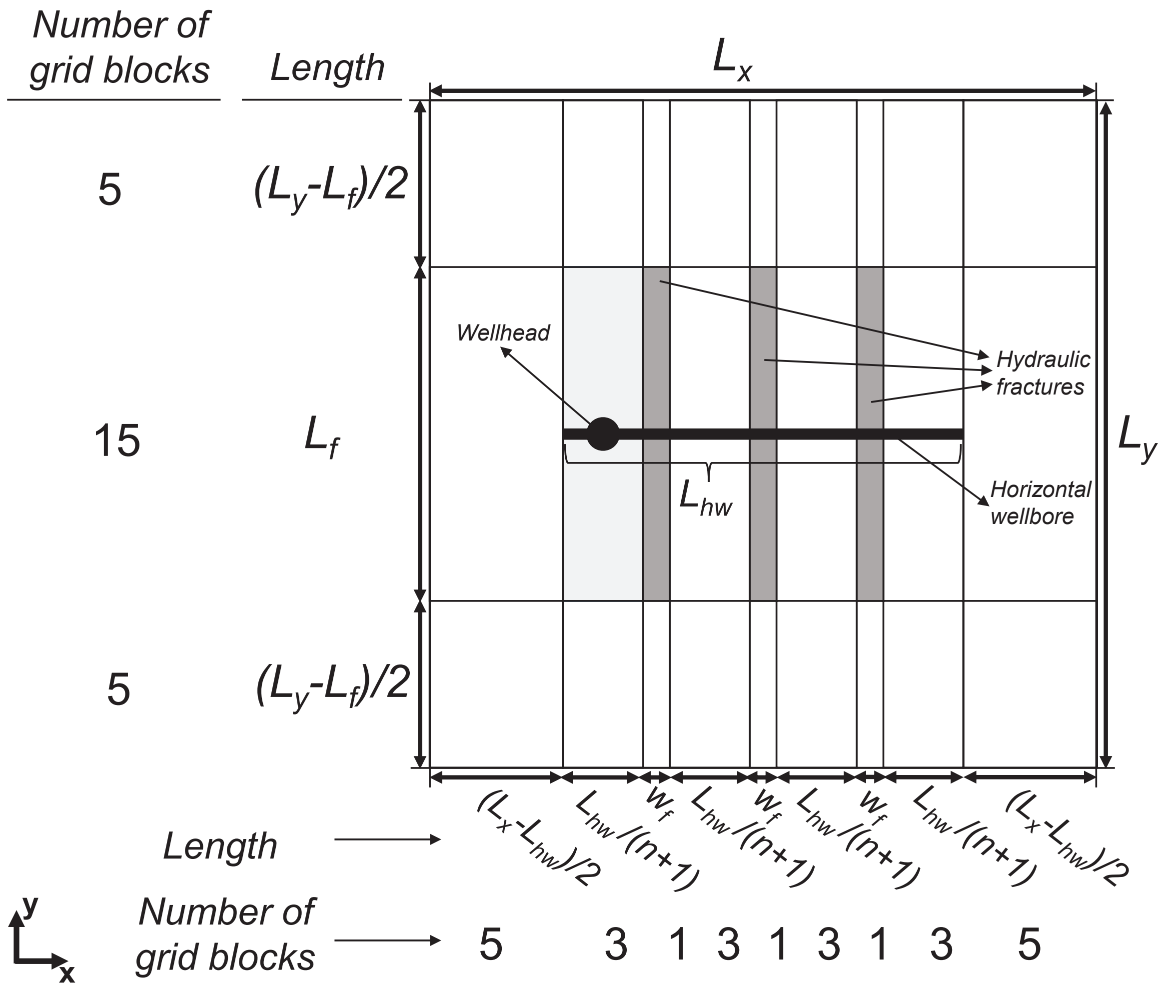


Numerical Reservoir Model

- A tight-gas sand reservoir, with a horizontal well with multiple hydraulic fractures:



Representation of Production Performance

- After carefully investigating the possible use of various decline curves such as the 2nd order exponential decline curve, the power law loss-ratio rate decline curve, logarithmic decline curve with 4 parameters; Arps' hyperbolic decline curve is selected:

$$q = \frac{a}{(1 + bt)^c}$$

- Coefficients a, b, and c were used as the performance characteristics for the tight-gas model
- Using these coefficients provides the flexibility of obtaining the performance characteristics at any desired time scale

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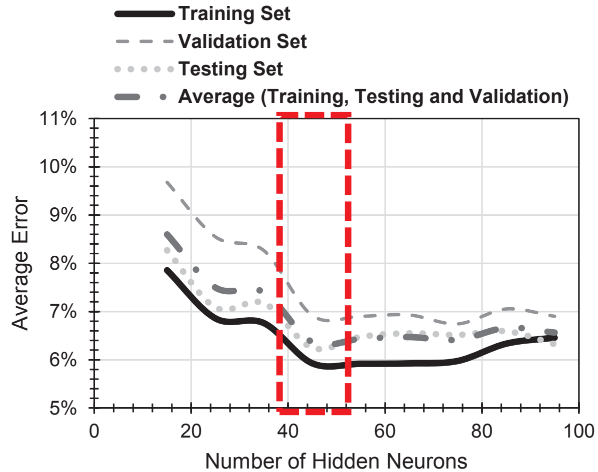
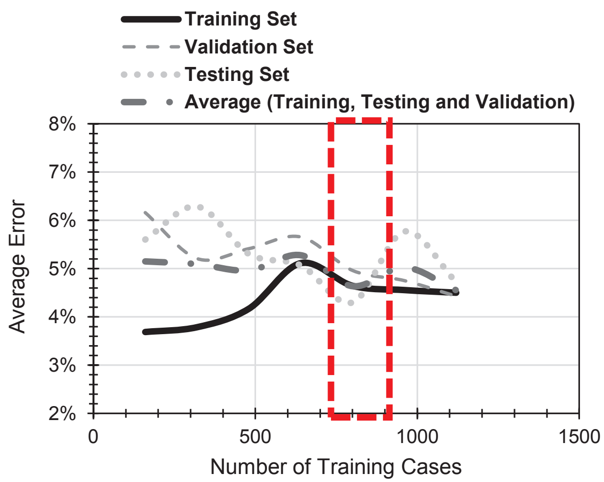
Input/Output Parameters

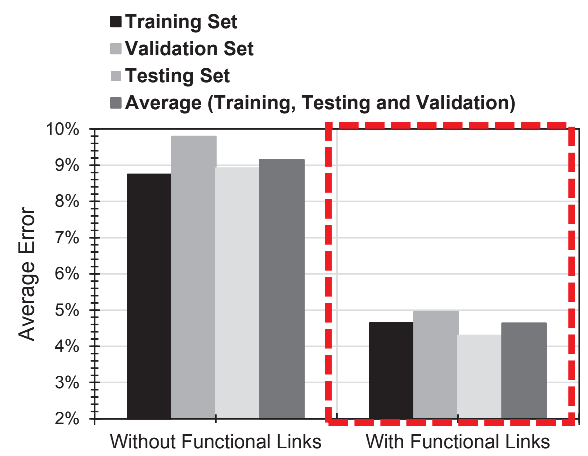
Parameter	Minimum value	Maximum value	Unit
Initial conditions of the reservoir			
Area (A=$L_x \times L_y$)	40	2,000	acres
Reservoir temperature (T)	80	280	F°
Initial reservoir pressure (p_i)	1,000	8,000	psi
Reservoir characteristics (Uncontrollable parameters related to reservoir and hydraulic fracture effectiveness)			
Thickness (h)	50	400	ft
Permeability (k)	0.000001	0.1	md
Porosity (ϕ)	3	25	%
Fracture length (L_f)	400	2,000	ft
Fracture permeability (k_f)	1,000	100,000	md
Fracture width (w_f)	0.1	0.4	inches
Operational parameters (Controllable parameters related to horizontal well and hydraulic fracture design)			
Flowing bottom-hole pressure (p_{wf})	14.7	$0.5p_i$+14.7	psi
Number of fractures (n)	1	30	
Horizontal wellbore length (L_{hw})	1,000	8,000	ft

Forward Model Design

- A cascade-forward network, with scaled conjugate-gradient backpropagation algorithm, 800 training cases
- 3 hidden layers, with 16-15-14 neurons, with functional links







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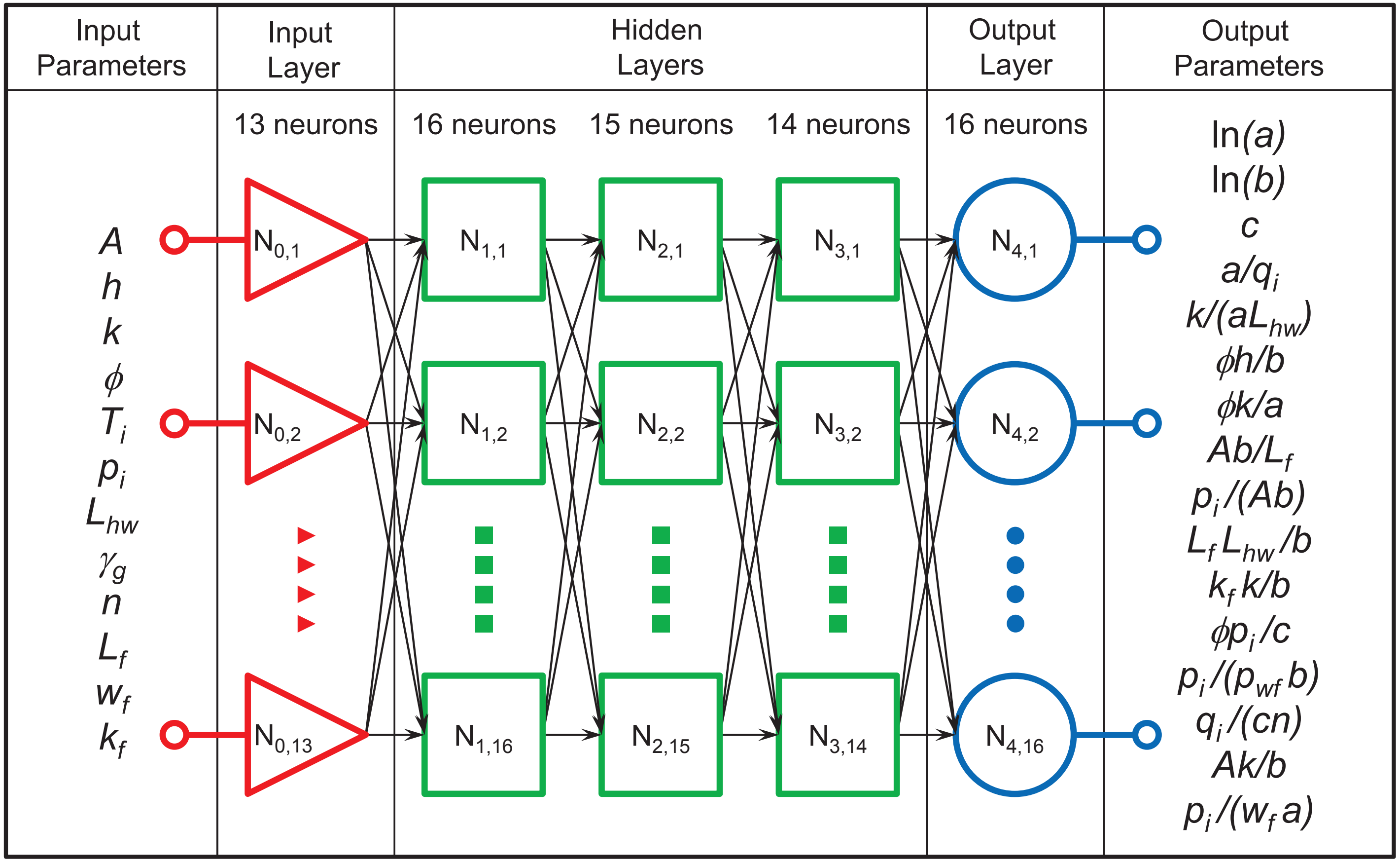
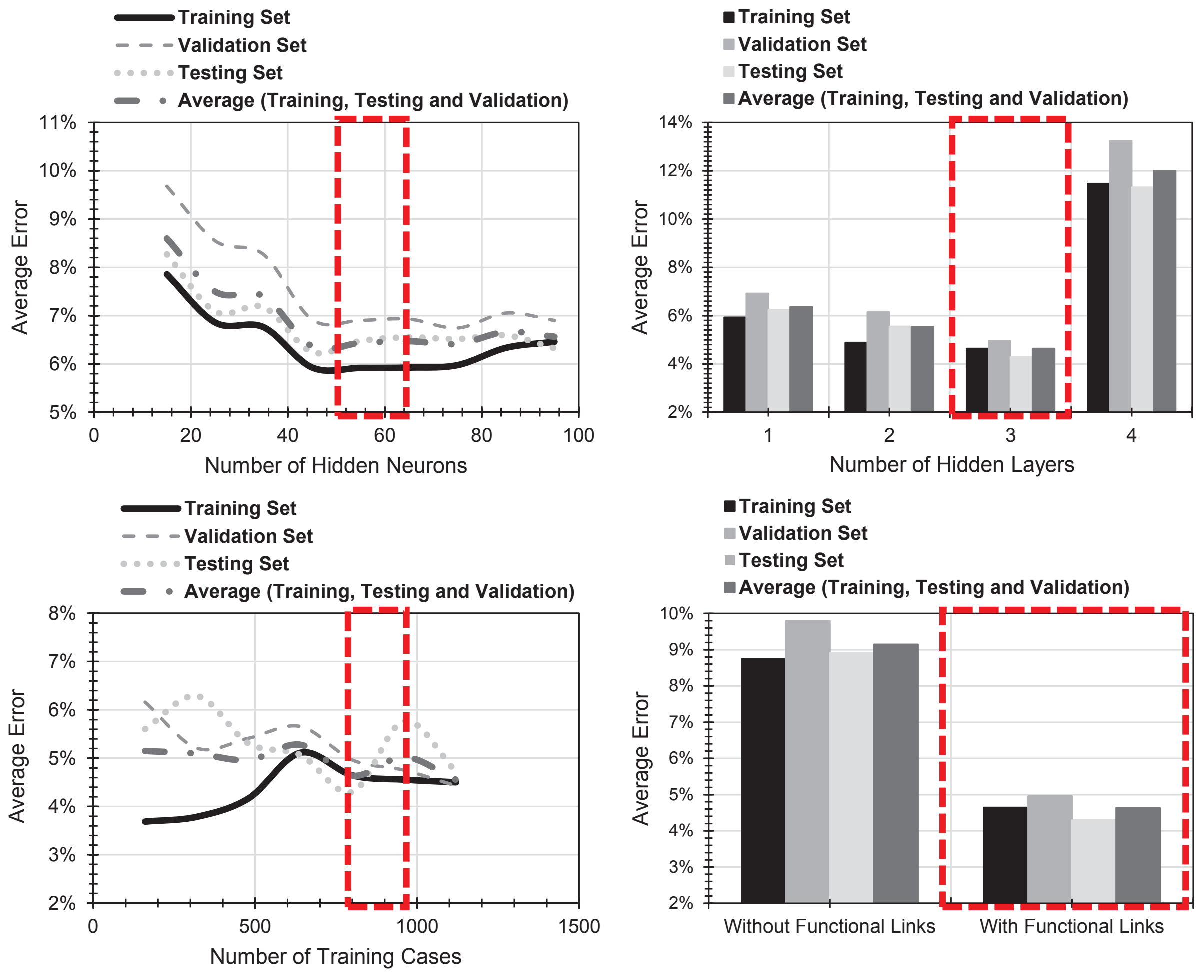
Forward Model Topology

- Given reservoir characteristics, operational parameters and initial conditions, expected performance of the horizontal well is predicted:



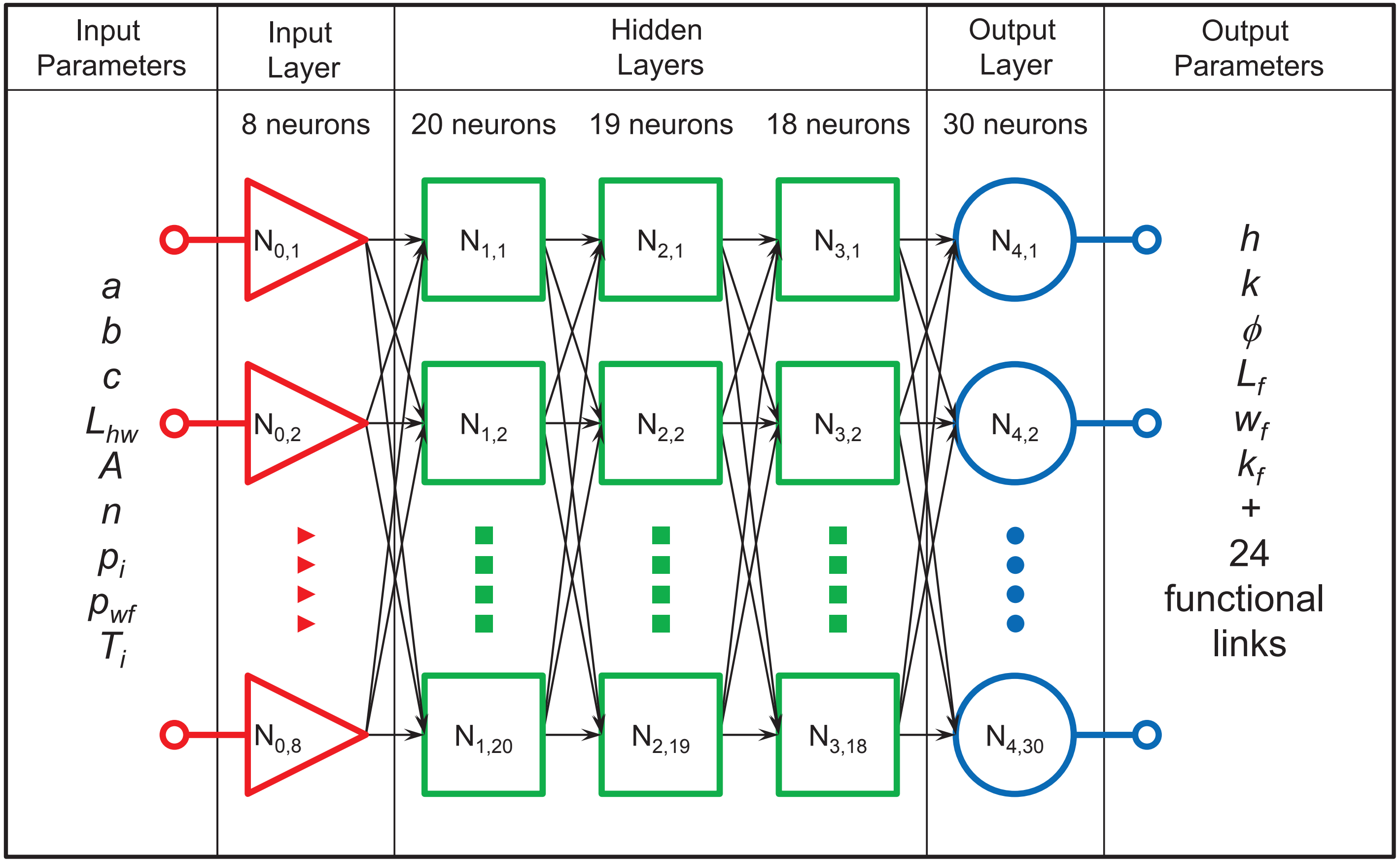
Inverse Model Design

- A cascade-forward network, with scaled conjugate-gradient backpropagation algorithm, 960 training cases
- 3 hidden layers, with 20-19-18 neurons, with functional links:

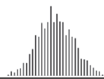
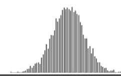


Inverse Model Topology

- Given observed performance of the horizontal well, operational parameters and initial conditions, reservoir characteristics are predicted:



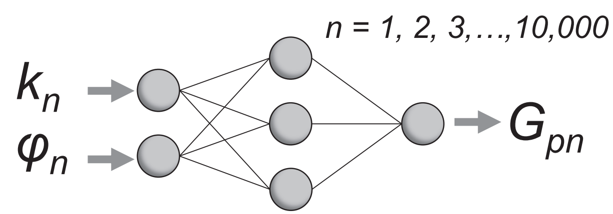
Probabilistic Assessment

	k, md	*φ*
Minimum	0.05	0.08
Most Likely	0.07	0.11
Maximum	0.1	0.14
Distribution	Triangular 	Normal 

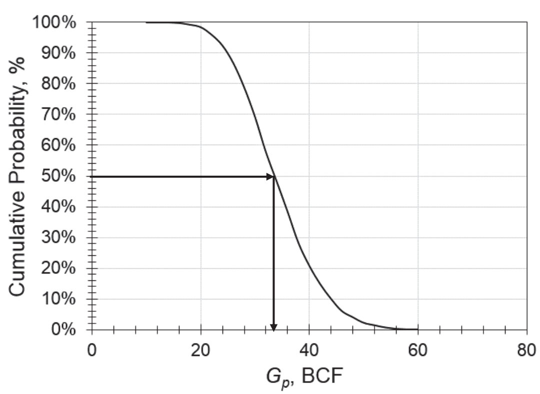
1. Assign probability distributions and ranges (minimum, maximum and most likely of uncertain input parameters.

n	*k, md*	*φ*
1	0.05	0.095
2	0.075	0.013
3	0.04	0.081
4	0.06	0.089
⋮	⋮	⋮
10,000	0.042	0.0125

2. Generate a dataset of each uncertain parameter using a random number generation algorithm such that it has the same probability distribution assigned in Step 1. Each set of parameters represents a case to run.



3. Predict the output parameters for each set of uncertain parameters using the data-driven forecasting tool.

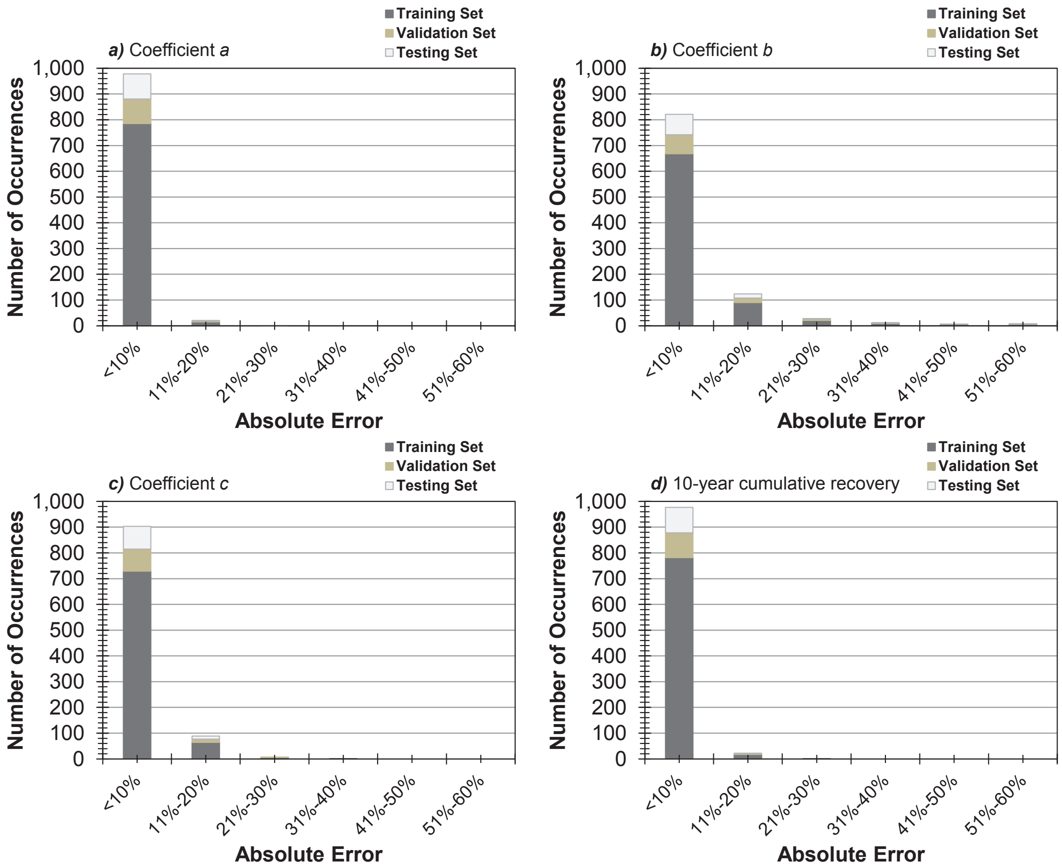


4. Analyze the cumulative probability distribution of the predicted output parameters and report the values that correspond to probabilities of interest.

Results & Discussion

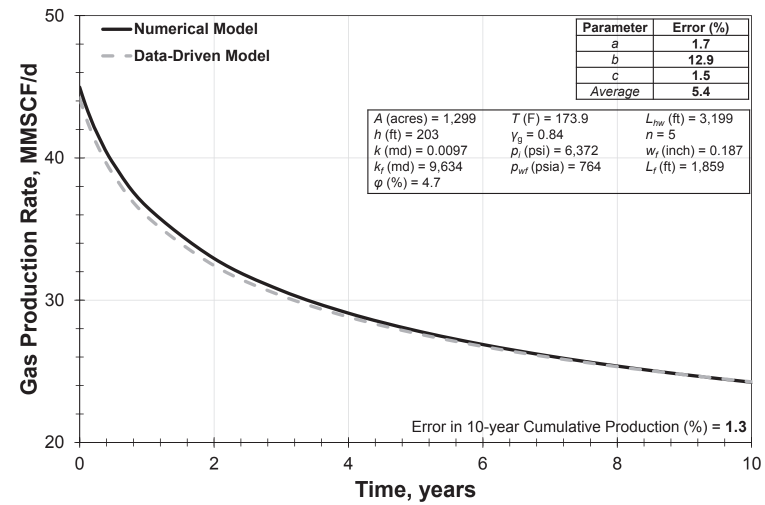
Forward Model: Prediction Errors

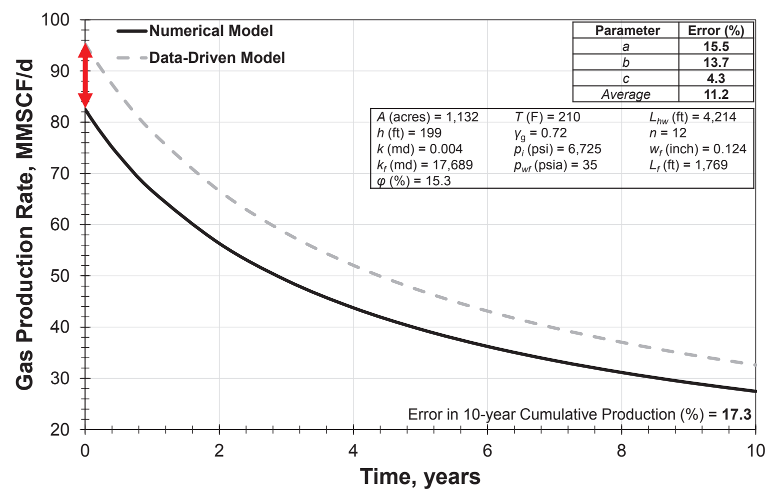
- Cumulative gas recovery of cases that were not shown during training are predicted with an 3.2% average-error.
- Decline-curve coefficients are predicted with an average error of 3.1-6.9%.



Forward Model: Cumulative Recovery

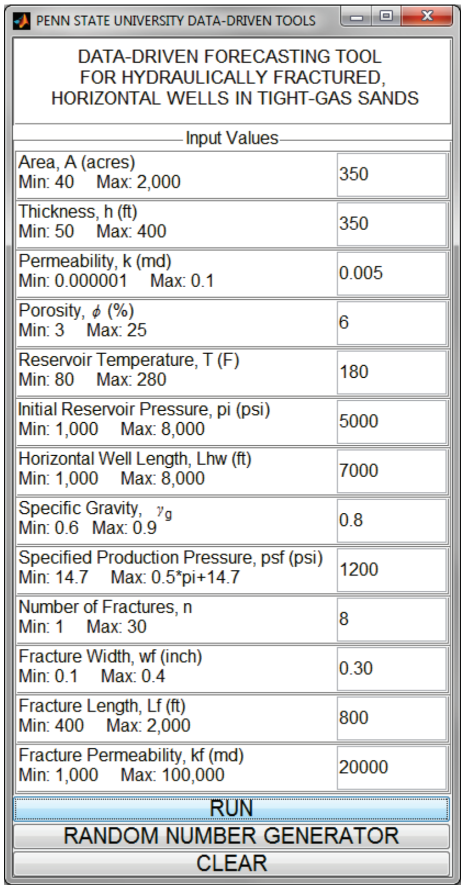
- Cumulative gas recovery after 10 years are predicted within 13% error range (3.2% on average)
- Accuracy of coefficient a (initial production rate) affected the match significantly
- Poorly predicted production performances follow similar patterns, regardless of coefficient a

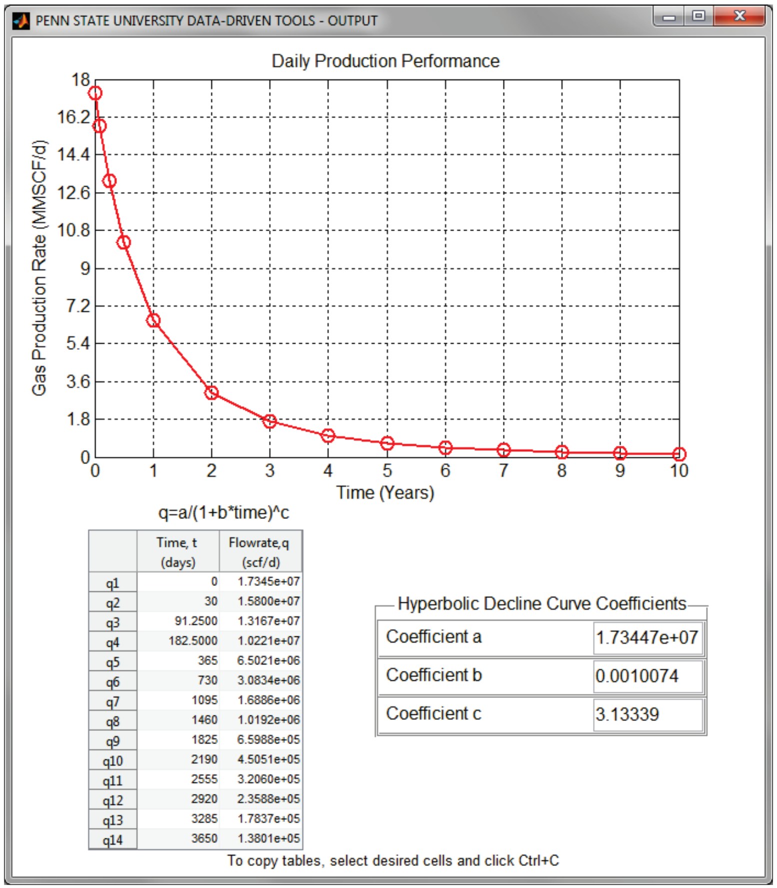




Forward Model: Graphical User Interface

- A graphical-user-interface is developed that allows to input the reservoir, hydraulic-fracture parameters and quickly outputs the expected performance





q=a/(1+b*time)^c

	Time, t (days)	Flowrate,q (scf/d)
q1	0	1.7345e+07
q2	30	1.5800e+07
q3	91.2500	1.3167e+07
q4	182.5000	1.0221e+07
q5	365	6.5021e+06
q6	730	3.0834e+06
q7	1095	1.6886e+06
q8	1460	1.0192e+06
q9	1825	6.5988e+05
q10	2190	4.5051e+05
q11	2555	3.2060e+05
q12	2920	2.3588e+05
q13	3285	1.7837e+05
q14	3650	1.3801e+05

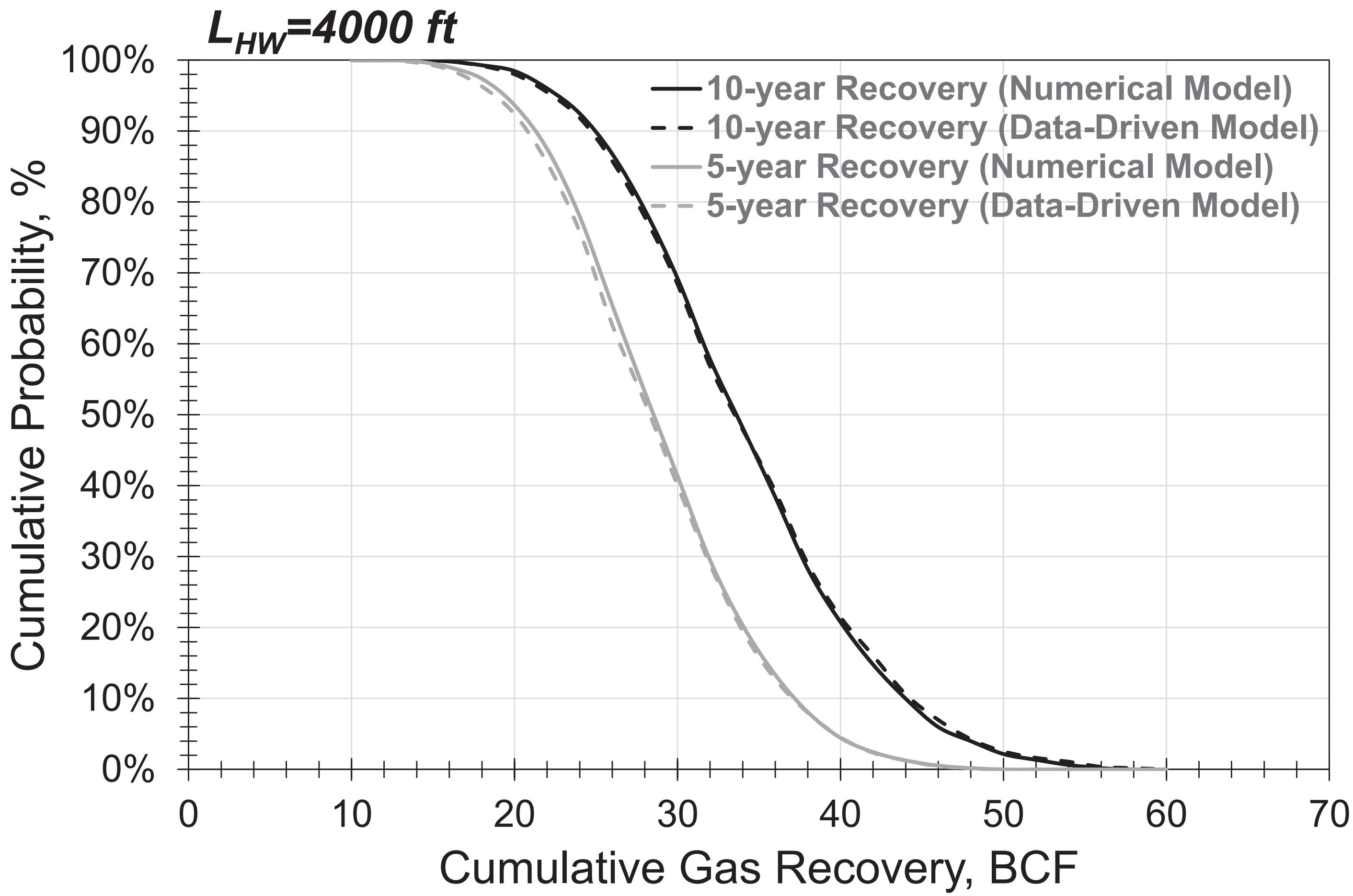
Hyperbolic Decline Curve Coefficients

Coefficient a	1.73447e+07
Coefficient b	0.0010074
Coefficient c	3.13339

To copy tables, select desired cells and click Ctrl+C

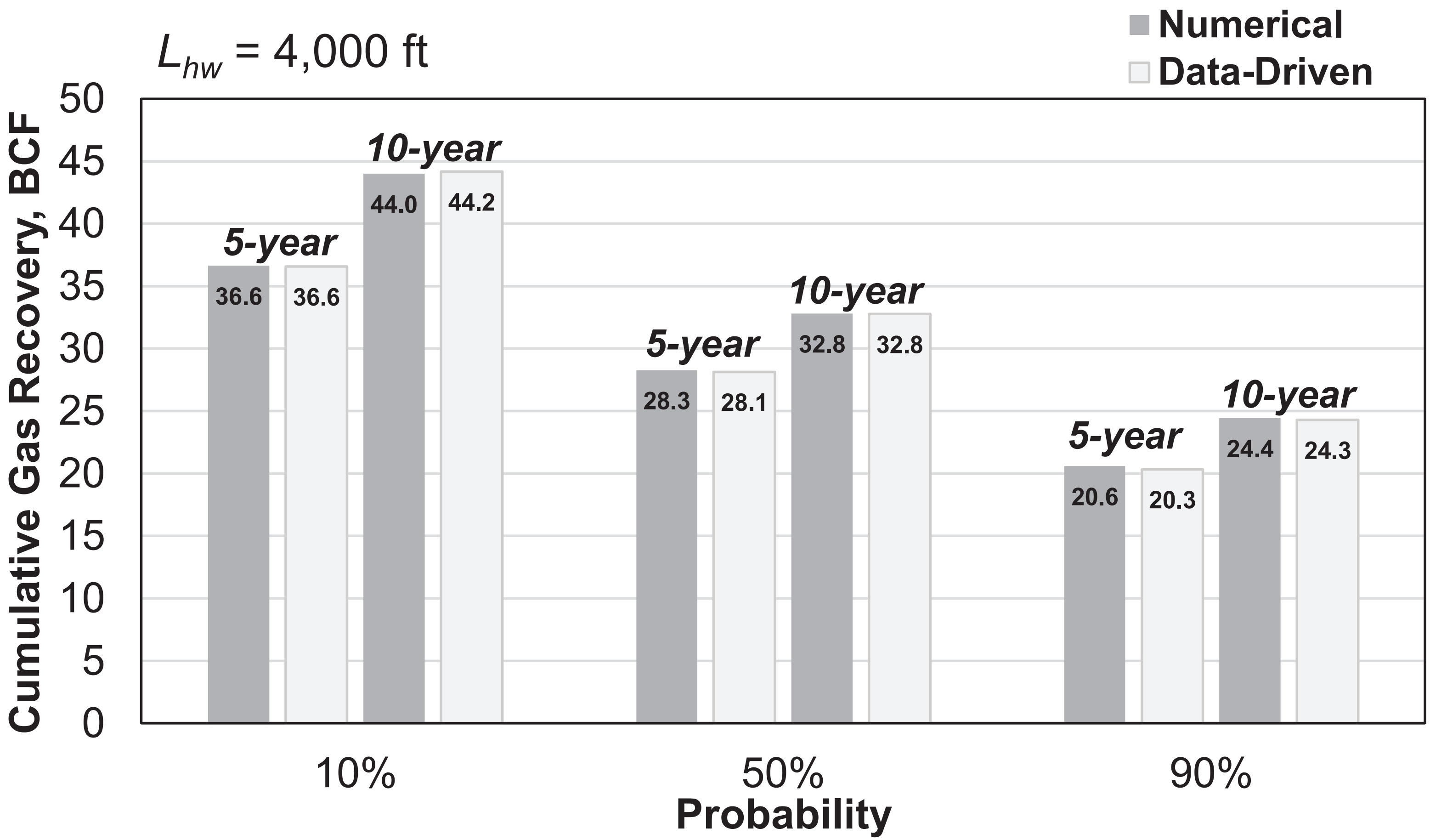
Forward Model: Probabilistic Assessment

- A probabilistic assessment of the performance of a typical Williams Fork Formation well through Monte Carlo Simulation:



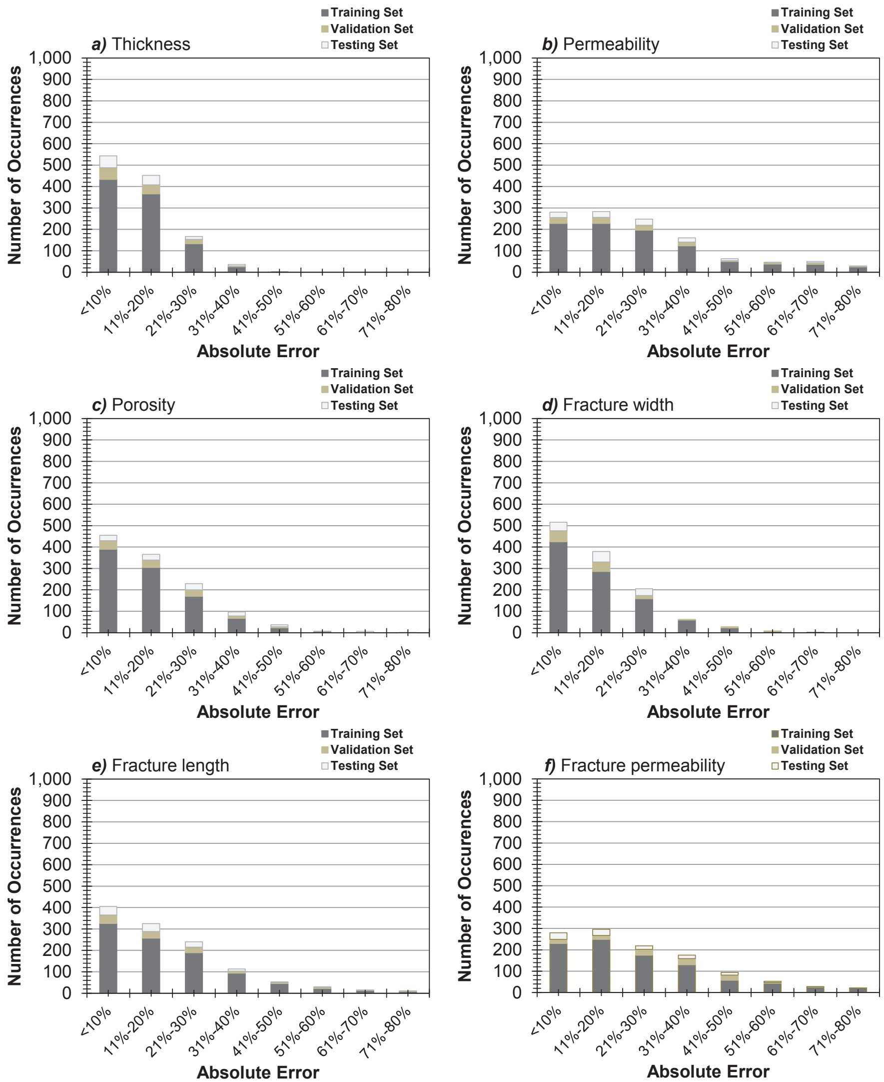
Forward Model: Probabilistic Assessment

- P10, P50, P90 estimates for 5-year and 10-year cumulative recoveries are in aggreement with numerical modeling results:

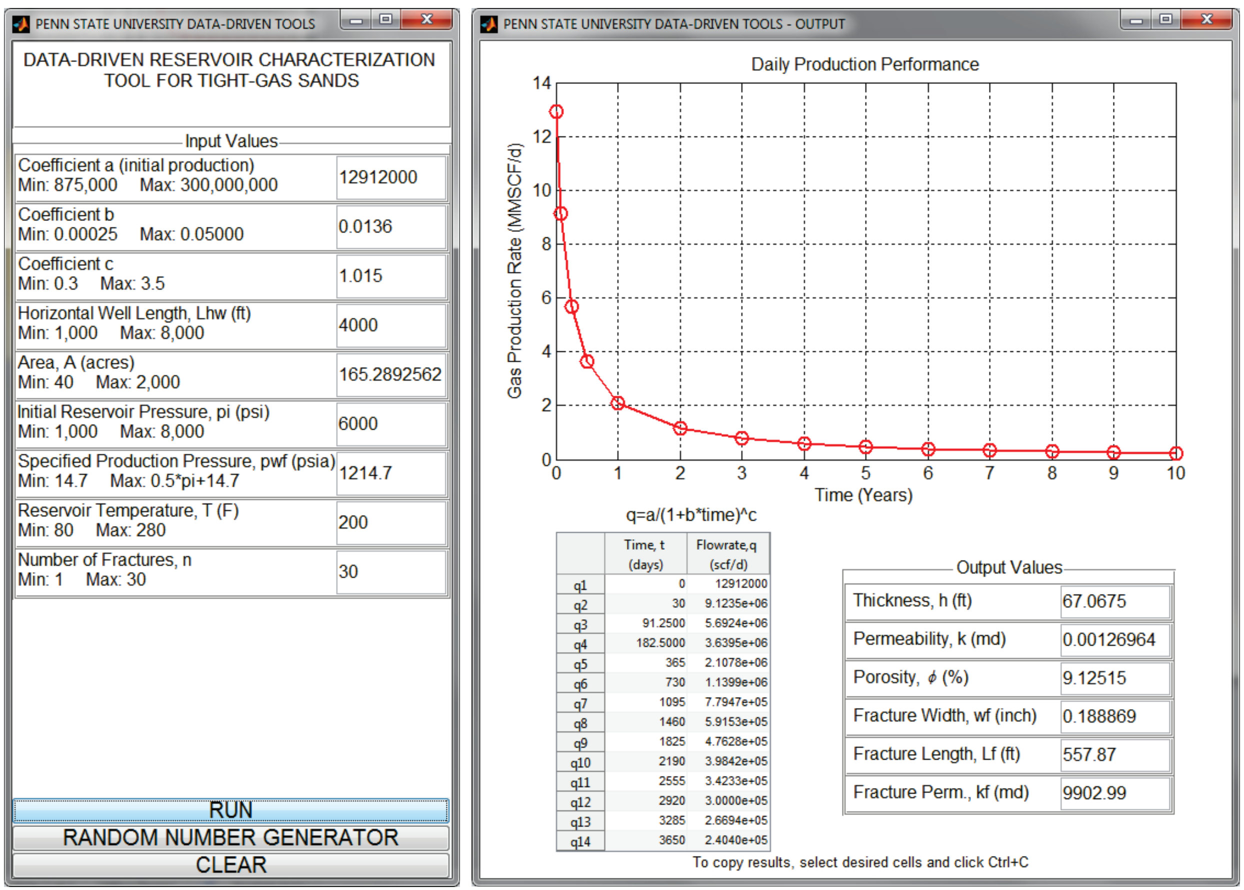


Inverse Model: Prediction Errors

- Mean of errors vary between 12.4% and 27.5%, with an average error of 19.8% for all parameters
- Frequency analysis: majority of cases were predicted within 20% error range
- Considering the inverse nature of the problem, acceptable errors are obtained for the purpose of reducing the uncertainty

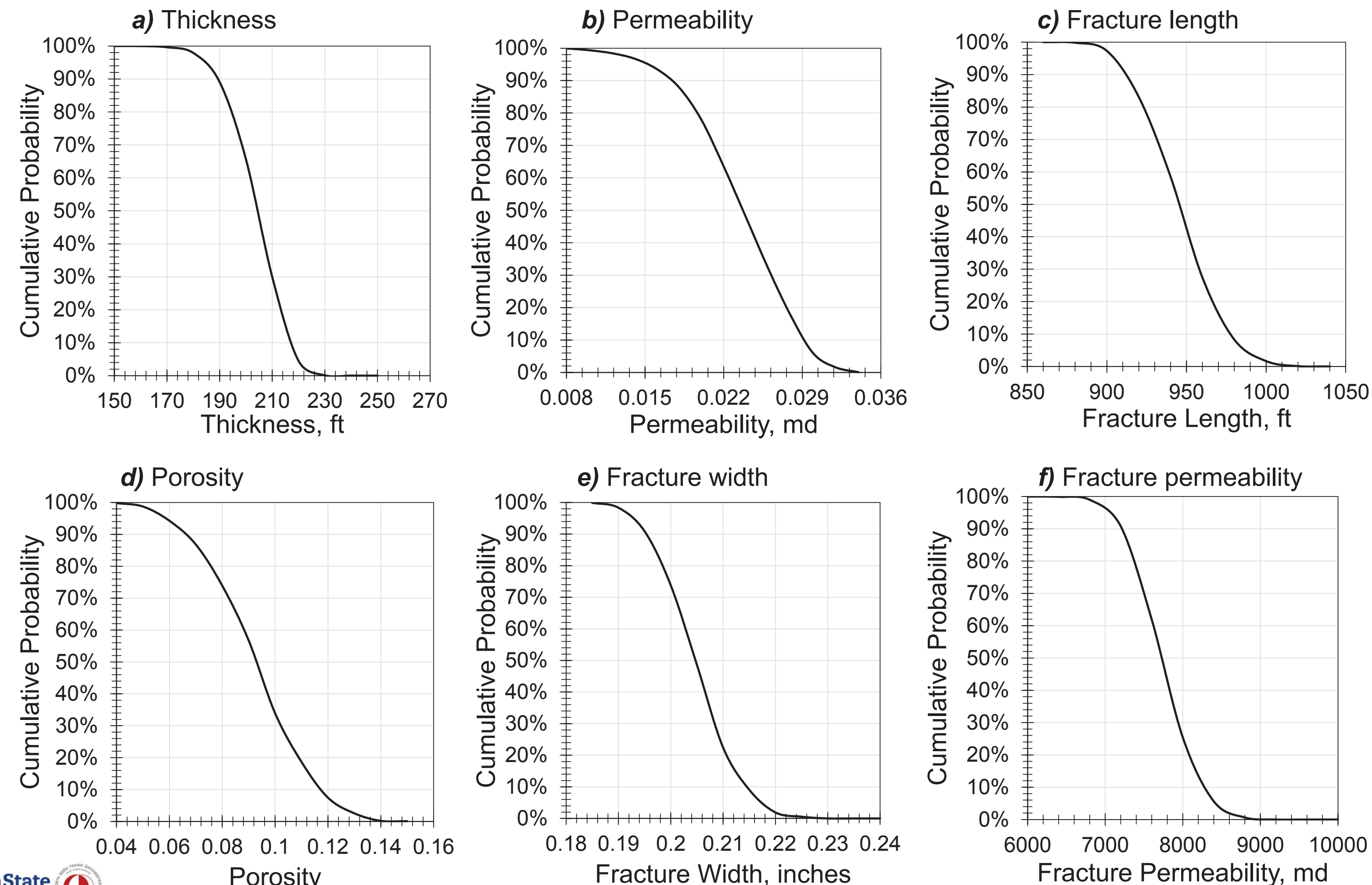


- A graphical-user-interface is developed that allows to input observed performance and known operational parameters, and outputs reservoir and hydraulic-fracture parameters (e.g. Granite Wash Reservoir, Texas):



Inverse Model: Probabilistic Assessment

- A probabilistic assessment of reservoir characteristics of Williams Fork Formation through Monte Carlo Simulation:



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Conclusions

Conclusions

- Screening tools are validated with blind cases:
  - Cumulative gas recovery after 10 years is predicted with an average error of 3.2%.
  - Reservoir/hydraulic fracture parameters are predicted with an average error of 19.8%.
- Inverse reservoir-characterization tool required more training cases, and a more complex topology, yet resulted in higher ranges of errors.
- These tools can be practically used as:
  - as a decision-making tool through the use of a graphical-user-interface application (outputting the expected quantities of the related parameters within a fraction of second)
  - as a probabilistic assessment tool as demonstrated with the case study for Williams Fork Formation

Thank You...

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Turgay Ertekin, Penn State U.

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Morgantown, West Virginia