2015

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Geoscience Frontiers 7 (2016) 11–20

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Contents lists available at ScienceDirect

China University of Geosciences (Beijing)

Geoscience Frontiers

journal homepage: www.elsevier.com/locate/gsf

Research paper

Full field reservoir modeling of shale assets using advanced data-driven analytics

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ARTICLE INFO

Article history:
Received 19 July 2014
Received in revised form
26 November 2014
Accepted 6 December 2014
Available online 23 January 2015

Keywords:
Reservoir modeling
Data driven reservoir modeling
Top-down modeling
Shale reservoir
Modeling
Shale

ABSTRACT

Hydrocarbon production from shale has attracted much attention in the recent years. When applied to this prolific and hydrocarbon rich resource plays, our understanding of the complexities of the flow mechanism (sorption process and flow behavior in complex fracture systems - induced or natural) leaves much to be desired. In this paper, we present and discuss a novel approach to modeling, history matching of hydrocarbon production from a Marcellus shale asset in southwestern Pennsylvania using advanced data mining, pattern recognition and machine learning technologies. In this new approach instead of imposing our understanding of the flow mechanism, the impact of multi-stage hydraulic fractures, and the production process on the reservoir model, we allow the production history, well log, completion and hydraulic fracturing data to guide our model and determine its behavior. The uniqueness of this technology is that it incorporates the so-called "hard data" directly into the reservoir model, so that the model can be used to optimize the hydraulic fracture process. The "hard data" refers to field measurements during the hydraulic fracturing process such as fluid and proppant type and amount, injection pressure and rate as well as proppant concentration. This novel approach contrasts with the current industry focus on the use of "soft data" (non-measured, interpretive data such as frac length, width, height and conductivity) in the reservoir models. The study focuses on a Marcellus shale asset that includes 135 wells with multiple pads, different landing targets, well length and reservoir properties. The full field history matching process was successfully completed using this data driven approach thus capturing the production behavior with acceptable accuracy for individual wells and for the entire asset.

1. Introduction

Much of the success in turning the shale source rock into an economically viable and producible hydrocarbon reservoir is accredited to George Mitchell and his team of geologists and engineers at Mitchell Energy & Development[1]. The success in production of shale oil and shale gas dates back to 1981 when multiple combinations of processes and technologies where examined before ultimately succeeding in 1997 with the use of a "slick-water" frac that made production from Barnett Shale economical and changed the future of the US natural gas industry (NGW, 2011). Today horizontal wells that include multi-stage, multi-cluster hydraulic fractures and pad drilling are the norm in developing shale oil and shale gas assets in North America and expanding throughout the world.

Shale reservoirs are characterized by extremely low permeability rocks that have a number of unique attributes, including high organic content, high clay content, extremely fine grain size, plate-like micro-porosity, little to no macro-porosity, and coupled Darcy and Fickian flow through the rock matrix. Unlike conventional and even tight sandstone gas reservoirs where all the gas is in the free state in the pore space, the gas in shale is stored by compression (as free gas) and by adsorption on the surfaces of the solid material, either organic matter or minerals (Guo et al., 2012).

This combination of traits has led to the evolution of hydraulic fracture stimulation involving high rates, low-viscosities, and large volumes of proppant. The stimulation design for plays such as Marcellus Shale is drastically different than anything else that has

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Peer-review under responsibility of China University of Geosciences (Beijing).
[1] Mitchell Energy & Development. Mitchell sold his company to Devon Energy in 2002 in a deal worth $3.5 Billion.

http://dx.doi.org/10.1016/j.gsf.2014.12.006
1674-9871/

been performed in the past. It takes large amounts of space, materials, and equipment to treat the Marcellus Shale to its fullest potential (Houston et al., 2009). Currently, the Marcellus shale, covering a large area in the northeastern US, is one of the most sought-after shale-gas resource play in the United States. It has presumably the largest shale-gas deposit in the world, having a potentially prospective area of 44,000 square miles, containing about 500 TCF of recoverable gas (Engelder, 2009).

This geological formation was known for decades to contain significant amounts of natural gas but was never considered economical. Uneconomic resources, however, are often transformed into marketable assets by technological progress (Considine et al., 2009). Advances in horizontal drilling and multi-stage hydraulic fracturing have made the Marcellus shale reservoir a focal point for many operators. Nevertheless, our understanding of the complexities associated with the flow mechanism in the natural fracture and its coupling with the matrix and the induced fractures, impact of geomechanical properties and optimum design of hydraulic fractures is still a work in progress.

A vibrant and fast-growing literature that covers operational and technological challenges of production from shale oil and shale gas is currently thriving. The research includes all aspects of drilling, completion, and production as well as difficulties in formation evaluation/characterization, in modeling macro- and micro-scales of fluid transport, and in developing reliable reservoir simulators. Understanding reservoir properties like lithology, porosity, organic carbon, water saturation and mechanical properties of the rock, which includes stresses, and planning completions based on that

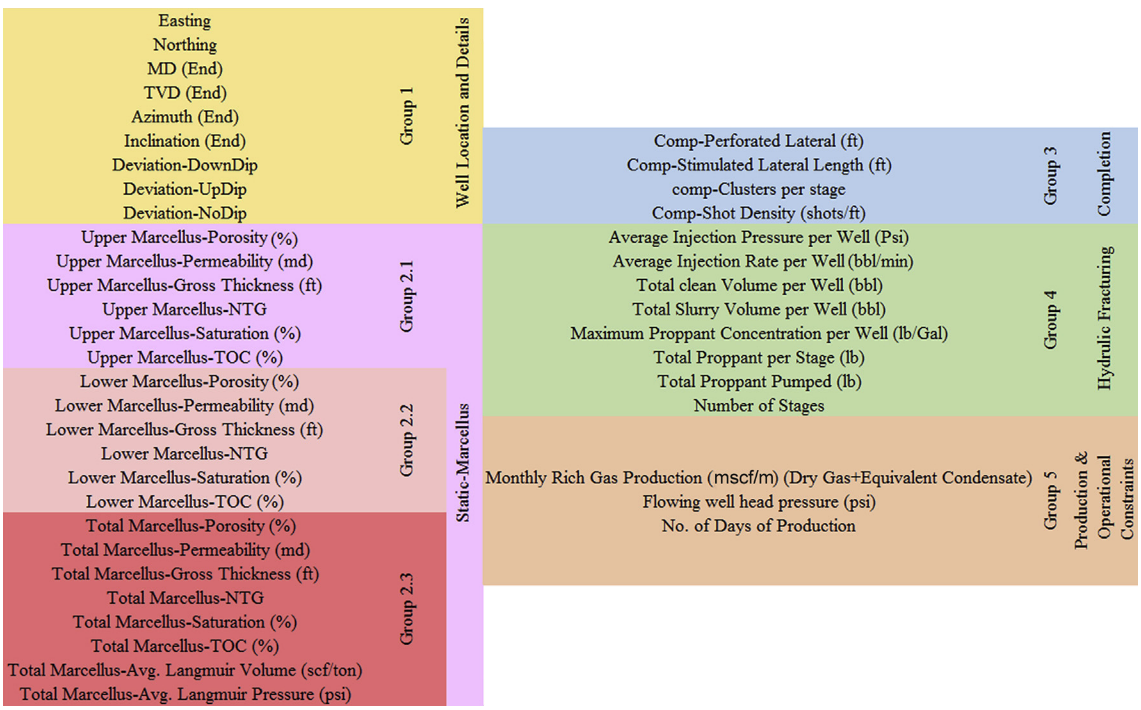

Figure 1. Data available in the dataset that include location and trajectory, reservoir characteristics, completion, hydraulic fracturing and production details.

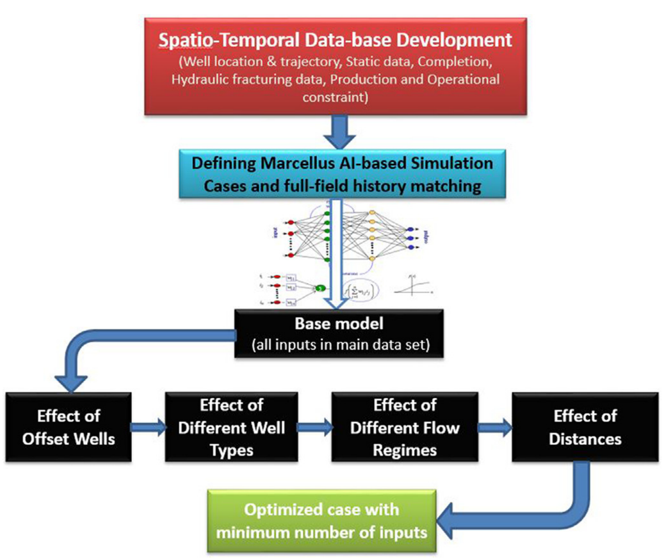

Figure 2. Marcellus shale AI-based Full-field history matching process.

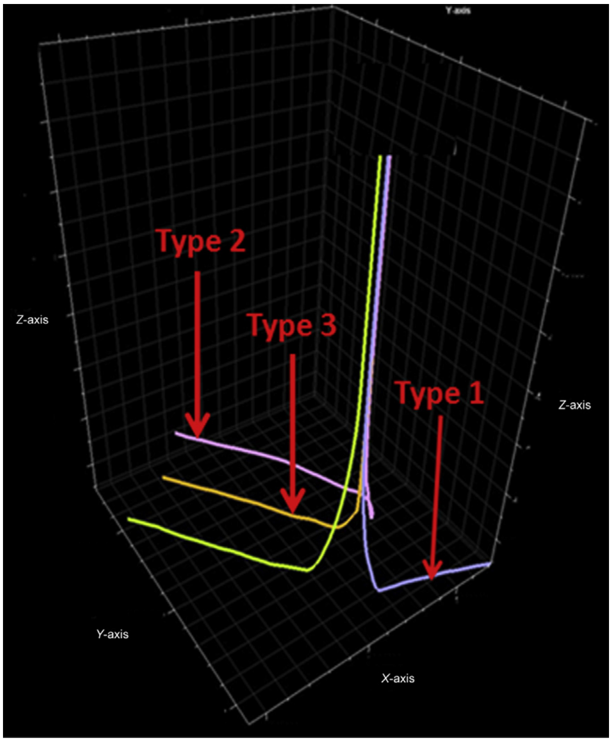

Figure 3. Three well types from a single pad.

knowledge is the key to production optimization. Therefore, the final objective is to increase our ability to integrate laboratory and petrophysical measurements with geochemical, geological, petrologic, and geomechanical knowledge, to develop a more solid understanding of shale plays and to provide better assessments, better predictions, and better models.

Reservoir simulation has played an important role towards achieving the abovementioned stated goals (Mohaghegh, 2013a). However there are still many challenges to overcome before reaching the stated goals. Firstly, the physics of fluid flow in shale rocks haven't been fully understood, and are undergoing continuous development as the industry learns more (Lee and Sidle,

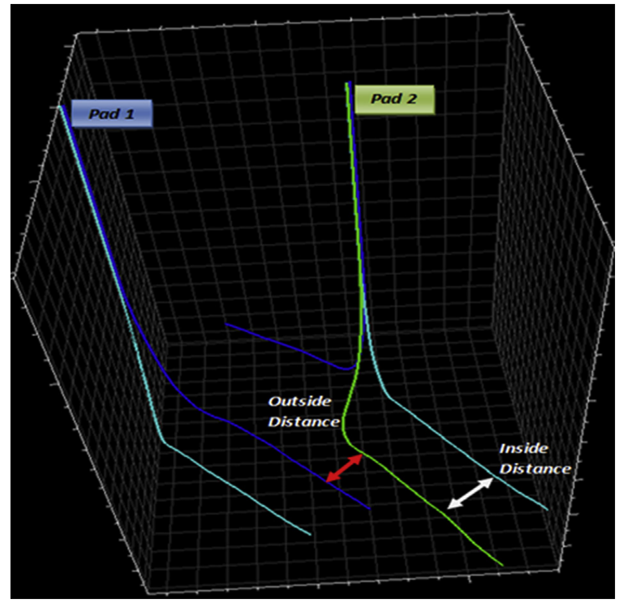

Figure 5. Inside and closest outside distance.

2010). Secondly, full reservoir simulation is resource intensive and time consuming. Thirdly, challenges encountered when applying conventional reservoir simulation to shale resources (Mohaghegh, 2013b) could be solved with pattern recognition technologies (Mohaghegh, 2000a,b,c).

In this paper, we developed an Artificial Intelligence-based model that is conditioned to all available field measurements (e.g. production history, measured reservoir characterizations including geomechanical and geochemical properties) as well as measured hydraulic fracturing variables like slurry volume, proppant amount and sizes, injection rate etc. Such model has the potential to provide operators with an alternative to history-match, predict and assess reserves in oil and gas producing shale reservoirs. The pattern recognition approach not only has a much faster turnaround time compared to numerical simulation techniques, but also offers reasonable accuracy while incorporating all available data compared to analytical and numerical techniques that are very selective in the type of field measurements that they use. The integrated framework

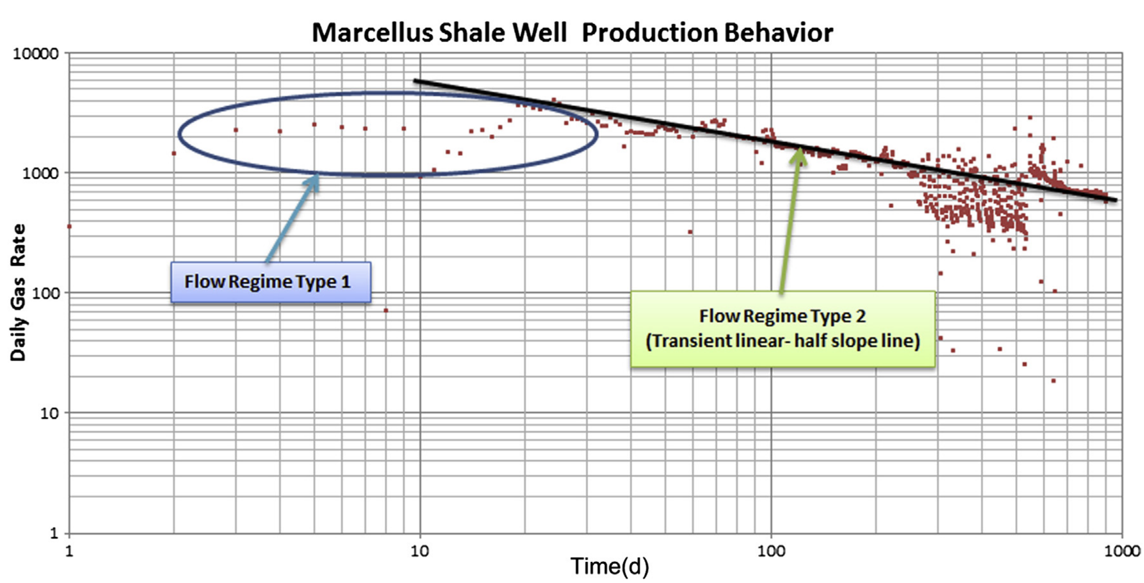

Figure 4. Log-log plot of production rate as a function of time for one of 135 wells in the asset studied for this paper.

presented in this paper enables reservoir engineers to compare and contrast multiple scenarios and propose field development strategies.

2. Top-Down modeling – pattern recognition based reservoir modeling

Artificial intelligence and data mining refers to a collection of tools and techniques that provide the means for finding patterns among non-linear and interdependent parameters involved in the shale oil and shale gas development process. Interest in the research of pattern recognition applications has spawned in recent years. Popular areas include: data mining (identification of a 'pattern', i.e., a correlation, or an outlier in millions of multidimensional patterns), document classification (efficient search of text documents), financial forecasting, and biometrics.

Top-Down modeling, a recently developed data-driven reservoir modeling technology (ISI, 2014), is defined as a formalized,

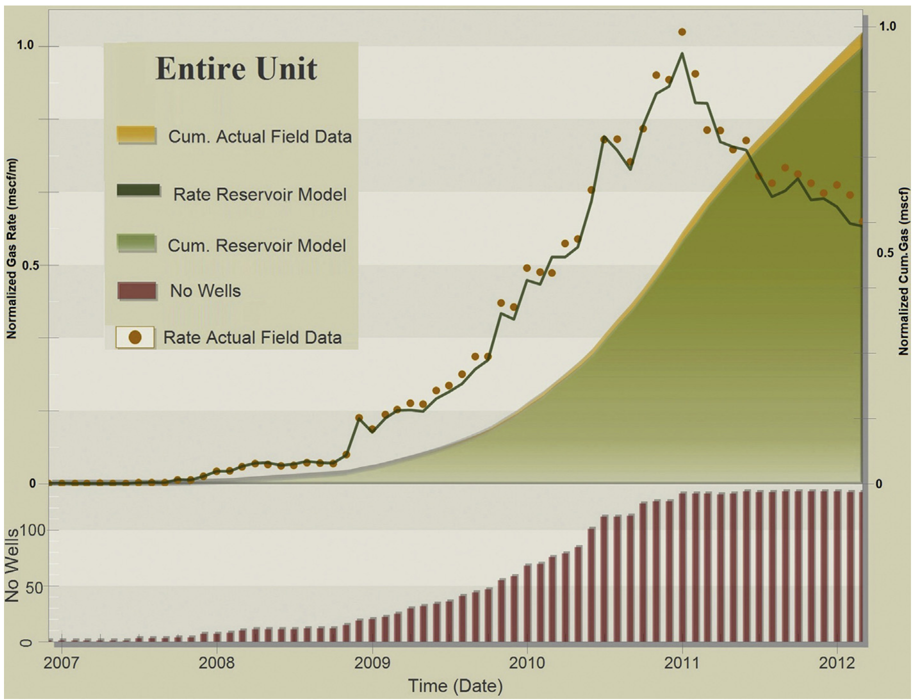

Figure 6. History matching result for entire field by using the maximum possible combination of parameters.

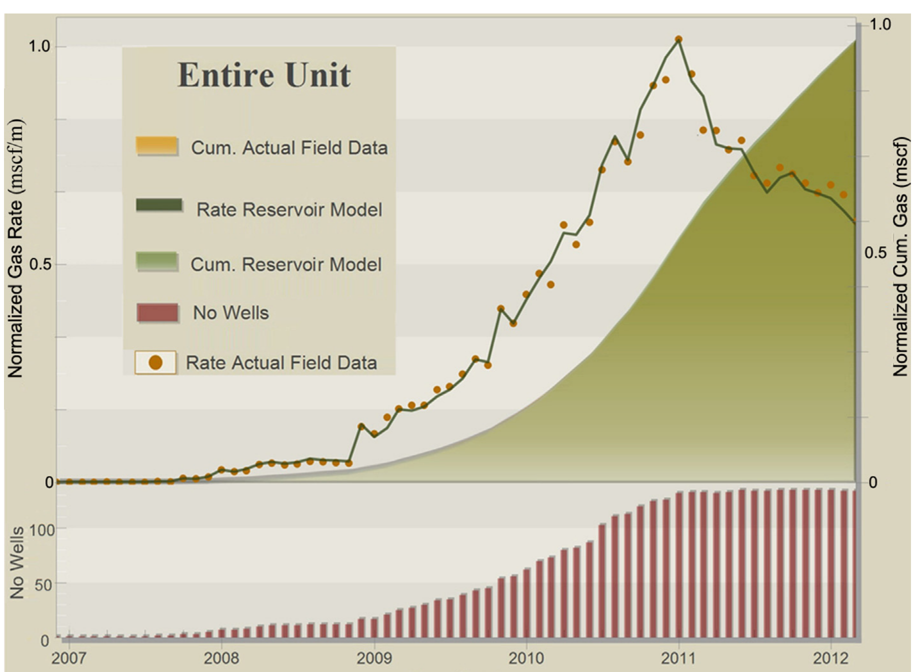

Figure 7. History matching result for entire field in optimum history matched model.

comprehensive, multi-variant, full-field, and empirical reservoir model, which takes into account all aspects of production from shale including reservoir characterization, completion and hydraulic fracturing parameters as well as production characteristics. Despite the common practice in shale modeling using a conventional approach, which is usually done at the well level (Strickland et al., 2011), this technique is capable of performing history matching for all individual wells in addition to full field by taking into account the effect of offset wells.

There are major steps in the development of a Top-Down shale reservoir model that is enumerated as follows:

• ***Spatio-temporal database development;*** the first step in developing a data driven shale reservoir model is preparing a representative spatio-temporal database (data acquisition and preprocessing). The extent at which this spatio-temporal database actually represents the fluid flow behavior of the reservoir that is being modeled, determines the potential degree of success in developing a successful model.

The nature and class of the AI-based shale reservoir model is determined by the source of this database. The term spatio-temporal defines the essence of this database and is inspired from the physics that controls this phenomenon (Mohaghegh, 2011). An extensive data mining and analysis process should be conducted at this step to fully understand the data that is housed in this database. The data compilation, curation, quality control and preprocessing is one of the most important and time consuming steps in developing an AI-based reservoir model.

• ***Simultaneous training and history matching of the reservoir model;*** in conventional numerical reservoir simulation the base model will be modified to match production history, while AI-based reservoir modeling starts with the static model and tries to honor it and not modify it during the history matching process. Instead, we will analyze and quantify the uncertainties associated with this static model at a later stage in the development. The model development and history matching in AI-based shale reservoir model are performed simultaneously during the training process. The main objective is to make sure that the AI-based shale reservoir model learns fluid flow behavior in the shale reservoir being modeled. The spatio-temporal database developed in the previous step is the main source of information for building and history matching the AI-based reservoir model.

In this work, an ensemble of multilayer neural networks is used (Haykin, 1999). These neural networks are appropriate for pattern recognition purposes in case of dealing with non-linear cases. The neural network consists of one hidden layer with different number of hidden neurons, which have been optimized based on the number of data records and the number of inputs in training, calibration and verification process (Mohaghegh, 2000a).

It is extremely important to have a clear and robust strategy for validating the predictive capability of the AI-based reservoir model. The model must be validated using completely blind data that has not been used, in any shape or form, during the development. Both training and calibration datasets that are used during the initial training and history matching of the model are considered non-blind. As noted by Mohaghegh (2011), some may argue that the calibration - also known as testing dataset -is also blind. This argument has some merits but if used during the development of the AI-based shale reservoir model can compromise validity and predictability of the model and therefore such practices are not recommended.

• ***Sensitivity analysis and quantification of uncertainties;*** during the model development and history matching that was defined above, the static model is not modified. Lack of such modifications may present a weakness of this technology, knowing the fact that the static model includes inherent uncertainties. To address this, the AI-based reservoir modeling workflow includes a comprehensive set of sensitivity and uncertainty analyses.

During this step, the developed and history matched model is thoroughly examined against a wide range of changes in reservoir characteristics and/or operational constraints. The changes in pressure or production rate at each well are examined against potential modification of any and all the parameters that have been involved in the modeling process. These sensitivity and uncertainty analyses include single- and combinatorial-parameter sensitivity analyses, quantification of uncertainties using Monte Carlo simulation methods and finally development of type curves. All these

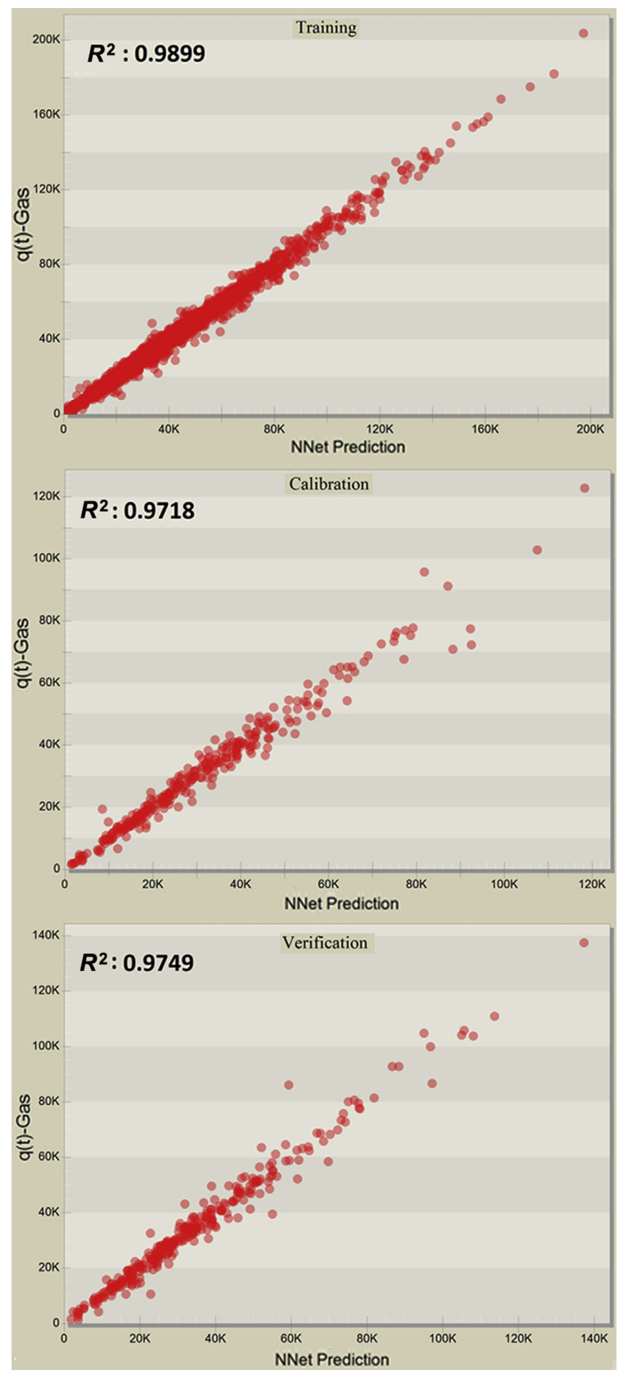

Figure 8. Data-driven full field reservoir model training, calibration, and verification cross plots.

analyses can be performed on individual wells, groups of wells or for the entire asset.

• ***Deployment of the model in predictive mode;*** similar to any other reservoir simulation model, the trained, history matched and validated AI-based shale reservoir model is deployed in predictive mode in order to be used for reservoir management and decision making purposes.

3. AI-based reservoir modeling in Marcellus shale

The study presented in this manuscript focuses on part of Marcellus shale that includes 135 horizontal wells within more than 40 pads. These horizontal wells have different landing targets, well lengths and reservoir properties. During the development of the Top-Down shale model all available data including static, dynamic, completion, hydraulic fracturing, operational constraint, etc. have been used for training, calibration, and validation of the model. A complete list of inputs that are included in main data set for development of the base model is shown in Fig. 1.

The data set includes more than 1200 hydraulic fracturing stages (approximately 3700 clusters of hydraulic fracturing). Some wells have up to 17 stages of hydraulic fracturing while others have been fractured with as few as four stages. The perforated lateral length ranges from 1400 to 5600 ft. The total injected proppant in these wells ranges from a minimum of about 97,000 lbs up to a maximum of about 8,500,000 lbs and total slurry volume of about 40,000 bbls to 181,000 bbls.

The wells are completed in both upper and lower Marcellus. The porosity of upper Marcellus varies from 5 to 10% while its gross thickness is measured to be between 43 and 114 ft. The total organic carbon content (TOC) of the upper Marcellus in this area is between 0.8 and 1.7%. The reservoir characteristics of lower Marcellus include porosity in the range of 8–14%, gross thickness between 60 and 120 ft, and TOC of 2–6%.

4. Results and discussion

During the training and history matching process using AI-based modeling approach inclusion and exclusion of multiple parameters were examined in order to determine their impact on model behavior. Fig. 2 includes a flowchart that shows the evolution process of developing the AI-based Marcellus shale full field reservoir model. It starts from the base model (where most of the parameters are included as our first shot) to converge to the best history matched model where optimum number of inputs are identified.

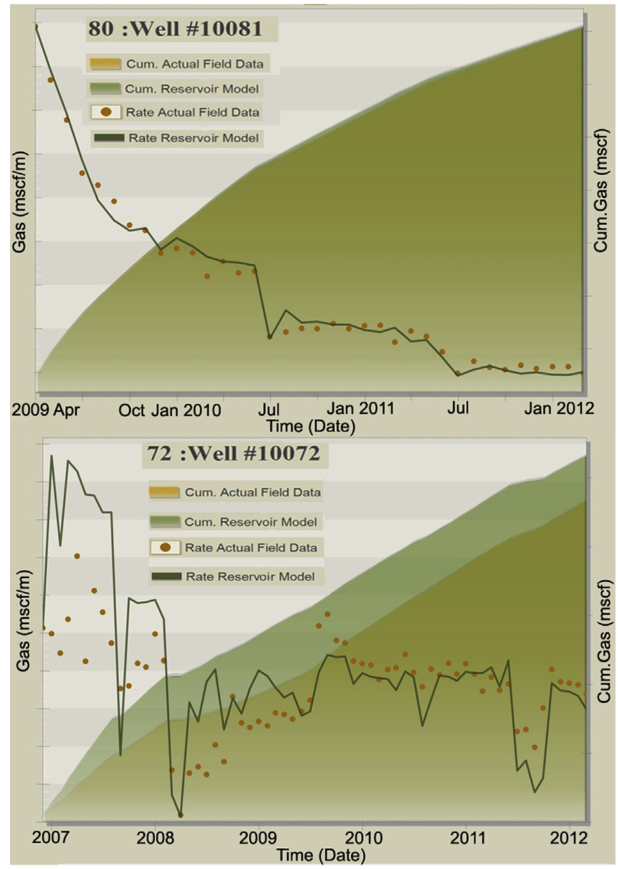

Figure 10. The best (top) and worst (bottom) history matched wells in the optimum history matched model.

4.1. Impact of different input parameters

Base Model – As illustrated in Fig. 2, the base model was built by incorporating all available data that are listed in Fig. 1. This model consists of all field measurements including well locations, trajectories, static data, completion, hydraulic fracturing data, production rates, and operational constraints.

Easting (Main Well and its offset) Northing (Main Well and its offset) MD (Main Well)	Group 1	Well Location	Breakdown Pressure (Main Well and its Offset) Total Slurry Volume per Well (bbl) (Main Well and its offset) Total Proppant Pumped (lb) (Main Well) Total Number of Clusters (Main Well)	Group 4	Hydraulic Fracturing
Porosity (%) (Main Well and its Offset) Net Thickness (Main Well and its Offset) Water Saturation(Main Well and its Offset) TOC (%)(Main Well and its Offset)	Group 2,3	Static-Marcellus	Monthly Rich Gas Production (mscf/m) (Dry Gas+Equivalent Condensate) Flowing well head pressure (psi) No. of Days of Production	Group 5	Production & Operational Constraints
Comp-Simulated Lateral length (ft)-(Main Well and its Offset)	Group 3	Completion	Flow Regimes (Main Well and its Offset) Inside and Outside Distances (Main Well) Well Type (Main Well and its Offset)	Group 6	Additional Parameters

Figure 9. List of the inputs in optimum history matched model.

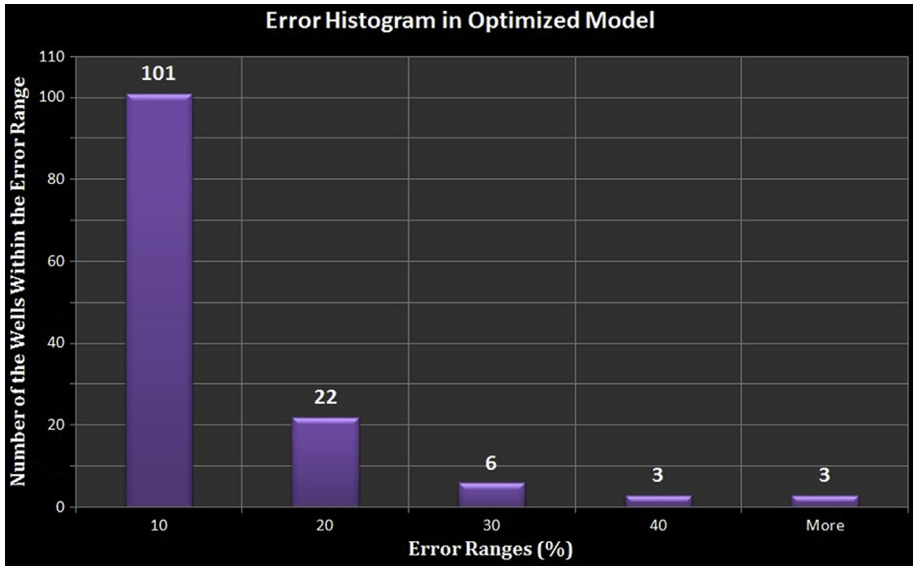

Figure 11. History matching error histogram for optimum history matched model.

Effect of Offset Well – In order to consider the effect of offset wells and taking into account for any well interference, all aforementioned properties for closest offset well were included in the modeling.

Effect of Different Well Types – Since drilling multiple wells from a pad is a common practice in the most shale assets and given the fact that the horizontal wells drilled from a pad experience different interaction with their offsets, three types of laterals have been defined. Fig. 3 shows the configuration of the three types of wells drilled from a single pad. Based on this definition a new parameter was added to the dataset marked as "Well-Type." This parameter was assigned values such as 1, 2, or 3 in order to incorporate the "Well-Type" information.

Following is a brief description of the three "Well-Types" used in the data-driven full field model.

- *Type one Lateral:* This type of lateral has no neighboring laterals and does not share drainage area. It does not experience any "Frac Hits[2]" from wells in the same pad (it might experience Frac-Hit from a lateral from an offset pad) and its reach will be as far as its hydraulic fractures.
- *Type two Lateral:* The type two lateral has only one neighboring lateral and therefore, it shares part of the drainage area and "Frac Hits" are possible from laterals in the same pad (it might experience Frac-Hit from a lateral from an offset pad).
- *Type three Lateral:* The type three lateral is bounded by two neighboring laterals thus, the drainage area will be shared and "Frac Hits" are possible from both sides in the same pad. If a type three lateral experiences a Frac-Hit from an offset pad, it will be from a different depth.

Effect of Different Flow Regimes – There are usually two distinct flow regimes that can be observed in all the wells. The first flow regime corresponds to the production of the initial free gas in the fracture/pore spaces, which is immediately available for production and it may last a few days to a few months (Flow regime type one). Most of the wells have been observed to exhibit transient linear behavior as the main flow regime (Flow regime type two).

This transient linear behavior is characterized by a one-half slope on a log-log plot of rate against time. The transient linear flow regime is expected to be caused by transient drainage of low-permeability matrix blocks into adjoining fractures (Bello and Wattenbarger, 2010). These two flow regimes where introduced in the data-driven full field model as dynamic property. Fig. 4 shows the two flow regimes for one of the wells from the asset described in this case study.

Effect of Distances Between Laterals – In order to consider the impact of the location (distance from other laterals in the same pad and closest lateral from an offset pad), two distances were defined and used in the data-driven full field model: (1) distance between laterals of the same pad, (2) distance to closest lateral of a different pad. This concept is illustrated in Fig. 5.

As mentioned earlier, the base model was developed with maximum number of inputs that were available. The results of the history matching of the base model are shown in Fig. 6. This figure shows the history matching results for the entire field. It must be noted that in the data-driven full field reservoir model the history match is performed on a well by well basis. In order to generate the history match for the entire asset, as shown in Fig. 6, productions from individual wells are summed (the field measurements as well as the Top-Down model) and are plotted.

The top plot in this figure is the history match (monthly production, the left y axis and the cumulative production, the right y axis). The bottom bar chart shows the well count (number of producing wells). In the top plot, the orange dots represent the actual monthly rate (normalized to protect confidentiality of data) for the entire field while the green solid line shows the AI-based model results. The orange area represents the actual cumulative production (normalized to protect confidentiality of data) while the green area corresponds to cumulative production generated by the AI-based model.

4.2. Optimum history matched model

Although, the history matching results drived by using the maximum combination of parameters (Fig. 6) have reasonable accuracy, it is preferable to reduce the number of input variables in data-driven models. As the number of inputs in a data-driven model increases, a certain level control over the model behavior

[2] Frac Hit is a phenomena that is encountered when producing shale assets. It happens when production from a given well is disrupted as a function of hydraulic fracturing activities in an offset well. In a Frac Hit the water used during the hydraulic fracturing of an offset shows up and sometimes even completely shuts-in the producing well.

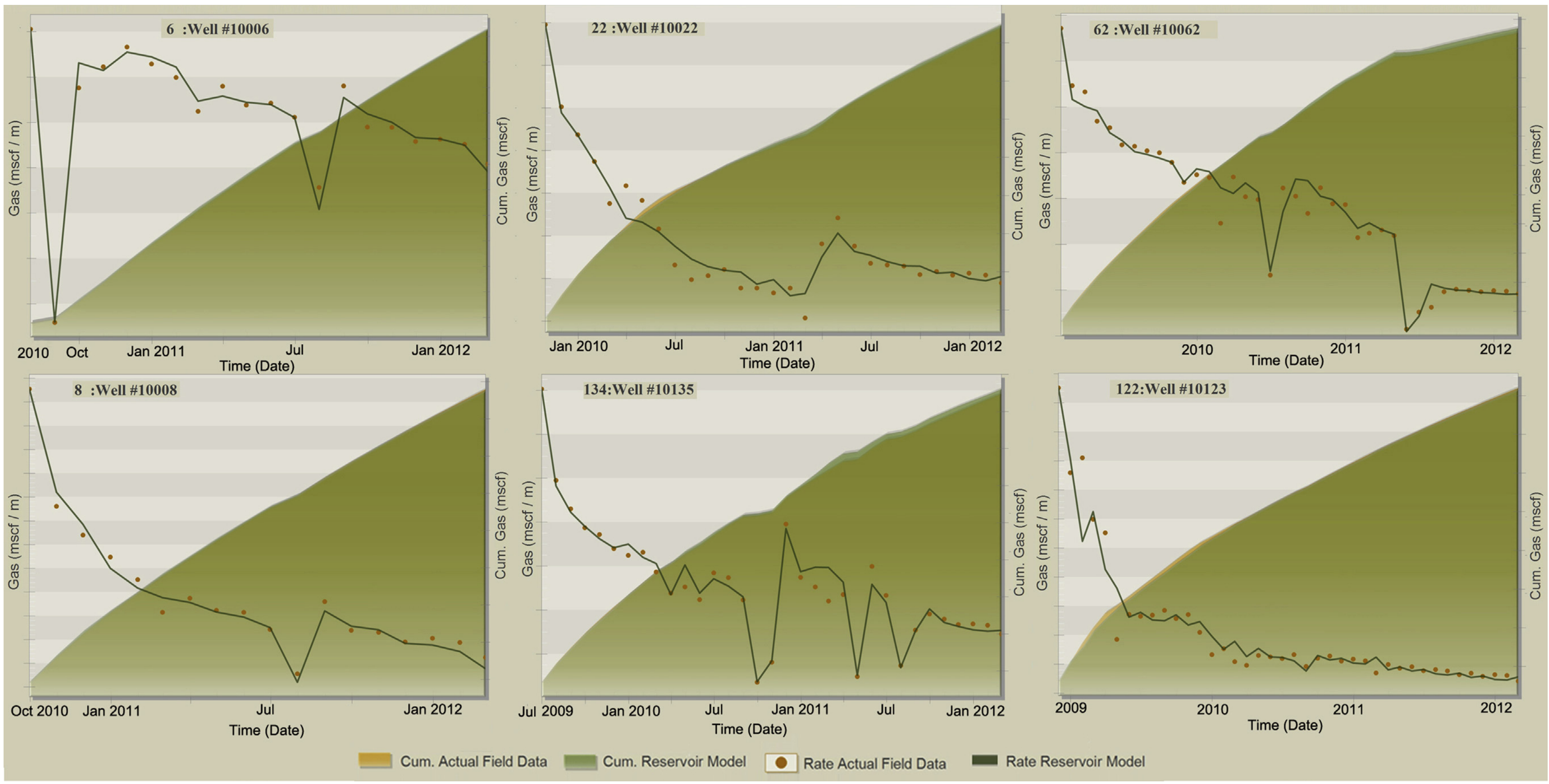

Figure 12. Examples of history matching results—excellent matches.

may be compromised. Accordingly, a history-matching process was derived with minimum combination of parameters that can/should be used to achieve an acceptable history match results for individual wells and for the entire field (the total number of inputs decreased from 103 to 38).

The inputs that were removed and the reason for removing these are as follows:

(1) The upper and lower Marcellus rock properties are drastically different so averaging them destroys a major geologic factor that affects both the fracing and the resulting the well performance. The lack of allocated production should not pose a problem and in fact the resulting AI model could be used to estimate the allocation of each zone and checking that result against the know reservoir properties. In most areas, you are supposed to see lower production from the upper Marcellus. This again could be used as an additional validation of the AI-based model.
(2) The perforated lateral length and total stimulated lateral length were included in the data set. Since the length of stimulated lateral is always 100 ft longer than the length of perforated lateral, therefore the total perforated lateral length was removed from the model.
(3) Instead of including stage based hydraulic fracturing data, the total values for slurry volume, proppant amount, etc. were used in the optimized case. In addition, the average injection rate and pressure that were not changing considerably were removed.
(4) Since the inside and closest outside distances from an offset were included for each individual well, therefore there was no need to include these two distances for offset well consequently they were removed from the input data.

The final history match result for the optimized model was improved and showed acceptable match of monthly gas rate and the cumulative production for the entire field (Fig. 7). For this case, 80% of the data was used for training and 20% for calibration and verification (10% for each). Fig. 8 shows the cross plot of the training, calibration, and verification of the data-driven full field reservoir model, which shows R^2 of 0.99, 0.97 and 0.97 for training, calibration and verification, respectively. In this figure, the x-axis is the predicated monthly gas rate by the model while the y-axis is the actual gas production rate from the field. Fig. 9 shows the list of

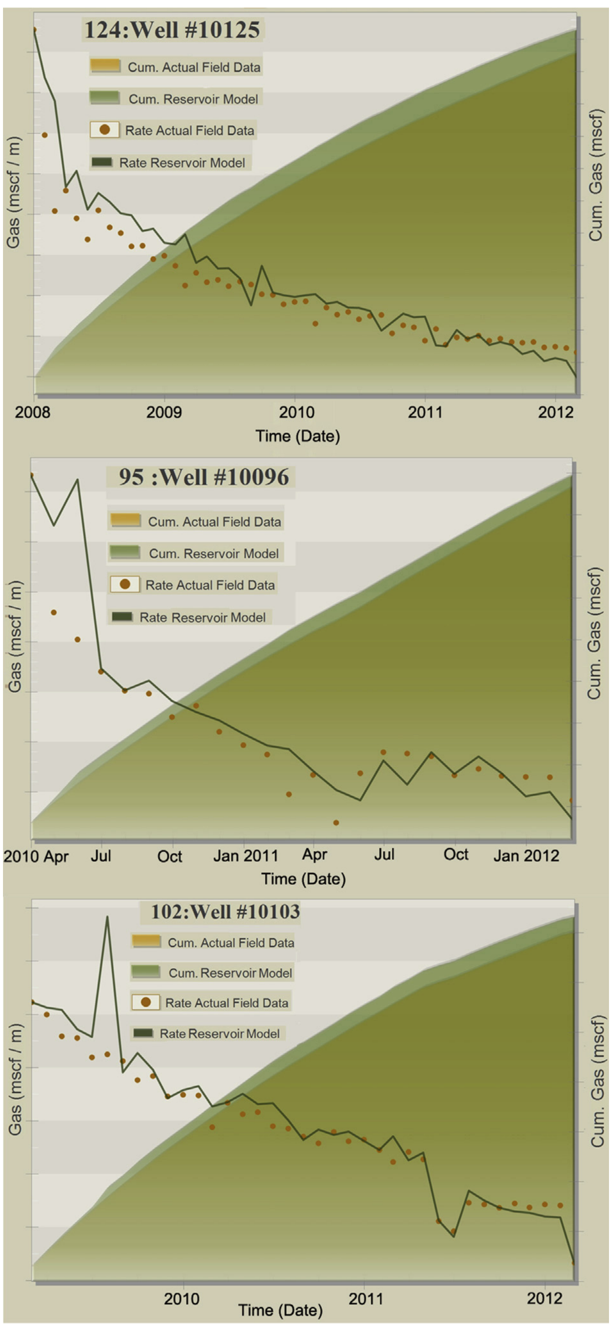

Figure 13. Examples of history matching results—good matches.

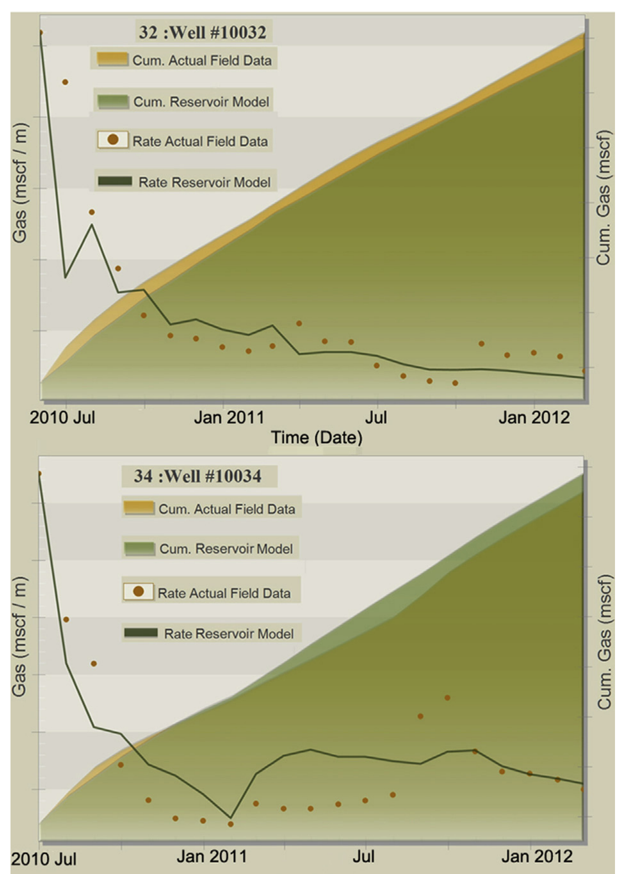

Figure 14. Examples of history matching results—average matches.

inputs that were used in optimum history matched model. Fig. 10 shows two wells with the best and the worst history matching results in the optimum history matched model. This figure shows that the erratic behavior displayed by the well in the graph on the right could not be captured by the data-driven full field reservoir model, even though the trend was followed.

4.3. Error Calculation

The error percentage of monthly gas production rate for all the 135 wells was calculated using the following equation:

$$\text{Error }(\%) = \frac{\sqrt{\frac{\sum_{t=1}^{Nt(i)}\left(Y_{i,t}^{\text{TDM}}-Y_{i,t}^{m}\right)^2}{Nt(i)}}}{\varDelta Y_i^m} \times 100$$

where, $Y_{i,t}^{\text{TDM}}$ is the predicted production by TDM (AI-based model);

$Y_{i,t}^{m}$ is the actual field data;
$\varDelta Y_i^m$ is the measured maximum change in actual production data;
$Nt(i)$ is the number of month of production.

Fig. 11 shows the histogram of error for the optimum history matched model. In this model, 101 wells were matched with less than 10% error (excellent), 22 wells had errors between 10 and 20% (good), 6 wells had errors between 20 and 30% (average) and 6 wells had errors of more than 40% (poor). Several example of excellent, good, average and poor history matching results are illustrated in Figs. 12–15.

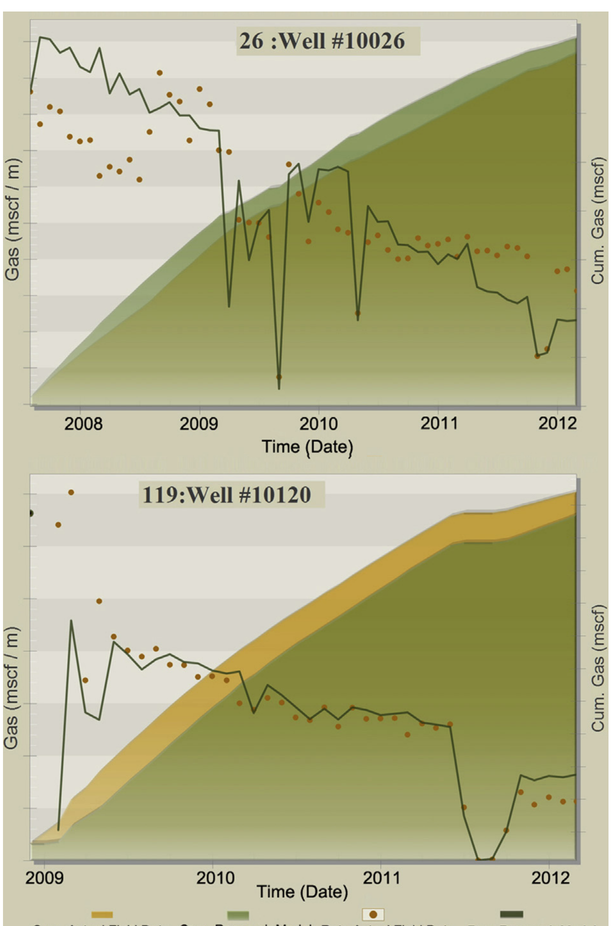

Figure 15. Examples of history matching results—poor matches.

5. Conclusion

In this paper, development and results of a data-driven, full field Marcellus shale reservoir model was discussed with the aim of overcoming the current issues associated with numerical simulation and modeling of shale gas reservoirs. The advantage of this technology is its capability of handling and incorporating hard data instead of a rigid representation of flow and transport mechanisms in shale reservoirs. When dealing with complex non-linear systems such as flow in shale reservoirs, the available hard data could identify its functional relationship using pattern recognition.

The full-field history matching was performed with acceptable accuracy. This model can be used for Marcellus shale wells and reservoir performance prediction and field development.

Acknowledgment

The authors would like to thank RPSEA and U.S. Department of Energy for partially funding this study. Authors would like to thank Range Resources Appalachia LLC for providing the data. We also thank and acknowledge Intelligent Solutions Inc. for providing IMagine™ and IDEA™ software packages for the development of the Top-Down models.

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