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Confirmation Of Data-Driven Reservoir Modeling Using Numerical Reservoir Simulation

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**CONFIRMATION OF DATA-DRIVEN RESERVOIR MODELING
USING NUMERICAL RESERVOIR SIMULATION**

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Thesis submitted
to the Benjamin M. Statler College of Engineering and Mineral Resources
at West Virginia University

in partial fulfillment of the requirements for the degree of
Master of Science in
Petroleum and Natural Gas Engineering

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2019

Keywords: Data-Driven Reservoir Modeling, Artificial Intelligence and Data Mining, Top-Down-Model

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ABSTRACT

CONFIRMATION OF DATA-DRIVEN RESERVOIR MODELING USING NUMERICAL RESERVOIR SIMULATION

Al Hasan Mohamed Al Haifi

Data driven reservoir modeling, also known as Top-Down Model (TDM), is an alternative to the traditional numerical reservoir simulation technique. Data driven reservoir modeling is a new technology that uses artificial intelligence and machine learning to build full-field reservoir models using field measurements (data - facts) instead of mathematical formulations that represent our current understanding of the physics of the fluid flow through porous media. TDM combines all field measurements into a comprehensive reservoir model to predict the production from each well in a field with multiple wells.

There are many opinions, speculations and criticism about not using the physics-based approach. Therefore, in this thesis, to confirm the capabilities of TDM, synthetic data generated from a numerical reservoir simulation model will be used for the development of a Data Driven Reservoir Model. That means, the physics of the fluid flow through porous media will be modeled using the generated data from the numerical reservoir simulation model which we know everything about.

In order to accomplish the objectives of this thesis a software application will be used for the development of the Top-Down Model. TDM will be developed (trained, calibrated and validated) and history matched using the data generated by a complex numerical reservoir simulation model in order to confirm the capabilities of the TDM in forecasting existing well behavior. Upon Completion of the TDM, predictions will be made using the developed TDM and are tested against the data that will be generated by the numerical reservoir simulation.

DEDICATION

This thesis is dedicated to my parents and my wife, for without their continuous support, none of this would have happened.

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First of all, I would like to offer my highest gratitude to God the Great for blessing me with the most precious gift – the joy of life, upon which without it, life would be bleak and meaningless.

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CHAPTER I

INTRODUCTION

1.1 GENERAL OVERVIEW

In numerical simulation and modeling, the numerical reservoir model is developed using available static and dynamic data. This flow model is based on the geological model. Considering the fact that the geo-cellular model is built using the geological and geophysical data, and then the upscaling process is performed, and the flow model is developed using the well-known engineering fluid flow principles followed by the history matching process, it can be asserted that it is “Bottom-Up” process. (Shahab D. Mohaghegh, S. Alireza Haghighat, Vida Gholami & David Moreno., April 2014).

In the traditional reservoir simulation, the major assumption that has to be made is that all the complexities of the reservoir are known and can be modeled in terms of the available mathematical equations. Therefore, if the production does not match the field measurements (observation) that results from the numerical simulation and modeling, it can be concluded that since the reservoir characterization is represented by a geo-cellular (static) model, developed by geoscientists, and is full of interpretations and uncertain values, we as engineers feel comfortable changing these numbers in order to get the match. This problem is even more challenging while dealing with unconventional reservoirs such as Shale. Many engineers believe it would be far from reality when it comes to modeling the physics of what happens in the Shale reservoirs and assert that, the mere reason to use the available models is simply because there is no alternative. (Mohaghegh, S. D., 2011, January)

Data-driven technologies are a set of new techniques that rely on data rather than our current understanding of the physical phenomena in order to build models, solve problems, and make recommendations and help us make decisions. In the context of reservoir engineering and reservoir modeling, data are also referred to as facts. This is based on the assumption that the measurements made in the field actually represent facts about the reservoir and the state of the fluid flow in it. It is well understood that measurements include noise and that noise, as an integrated part of the collected data, can be handled (Mohaghegh, Data-Driven Reservoir Modeling, 2017).

Data-driven reservoir-modeling development and analysis includes three phases (Mohaghegh, Data-Driven Reservoir Modeling, 2017). The first phase of the data-driven reservoir modeling, which is an exploratory analysis in nature, relates to the data mining. The second phase of data-driven reservoir modeling that is mainly concerned with the development (training, history matching, and validation) of a predictive reservoir model for the entire field is accomplished through artificial intelligence. The final phase of the data-driven reservoir modeling, which is the post-model analysis, includes a combination of both data mining and artificial intelligence. Since data mining is exploratory in nature, it mostly includes unsupervised algorithms. However, in the case of its application to reservoir engineering and reservoir modeling, some of the traditional unsupervised algorithms have been modified in order to incorporate reservoir engineering and geoscience domain expertise in the analysis.

1.2 PROBLEM STATEMENT

In order to efficiently develop and operate a petroleum reservoir, it is important to have a reservoir model. Nowadays, the only technique that is accepted and is being used in our industry is the reservoir numerical simulation. However, this technology is not accurate because it does not use the large amount of the available data from the mature fields. For example, if decline curve analysis is the tool that is being used to make decisions, it is obvious that no reservoir characteristics and no operational constraints are used during the decision-making process. Moreover, this tool is not fast, and it requires significant investment in time and manpower. Therefore, reservoir managers need tools that are accurate and fast in order to make decisions in a timely manner.

Data driven reservoir modeling, also known as Top-Down Model (TDM), provides a complete alternative to the numerical reservoir simulation model and can serve as an appropriate tool for reservoir management. The top-down model is a comprehensive, full-field, empirical reservoir model that does not modify the collection of the measured reservoir characteristics in order to history match multiple independent production variables. Therefore, synthetic data will be used in this study to confirm the capability of the TDM in forecasting existing well behavior.

CHAPTER II

LITERATURE REVIEW

2.1 DATA-DRIVEN TECHNOLOGIES

Mohaghegh defined the data-driven modeling as the process of applying artificial intelligence and data mining methods such as machine learning and pattern recognition in order to uncover hidden patterns in large data sets that represent fluid flow in porous media. Then, the discovered patterns are included into a comprehensive and cohesive full-field reservoir model with verifiable forecasting abilities that can be used to manage fields and their production (Mohaghegh, Data-Driven Reservoir Modeling, 2017). Data driven reservoir modeling is a new technology to build reservoir models that represent the fluid flow through porous media using filed measurements. The distinguishing feature of this technology is its data requirement for its analysis. Data-driven technology is completely based on field measurements that include well locations and trajectories, stimulations and completions, core data, well tests, well logs, seismic and production/injection history.

2.1.1 Data Mining

Data mining can be defined as the process of extracting a patterns (information) from a large quantities of data sets and transform these patterns into an understandable structure for further use. In data driven reservoir modeling, a comprehensive data set, also known as spatio-temporal database must be made before using any data driven algorithm. The spatio-temporal database should be large enough in order to discover the pattern in the data. Moreover, data cleaning has to be made for the spatio-temporal database to remove the errors, missing records and noise data.

As mentioned earlier, three phases are included in data-driven reservoir modelling, the first phase is exploratory analysis in nature, relates to the data mining. The second phase includes the development of a predictive reservoir model for the entire field using artificial intelligence. While, the third phase of the data-driven reservoir modelling is the post data analysis that includes a combination of both data mining and artificial intelligence (Mohaghegh, Data-Driven Reservoir Modeling, 2017).

2.1.2 Artificial Intelligence-Based Reservoir Modeling

Artificial Intelligence (AI) is a field of computer science which focus on creating machines that can engage on behaviours that humans consider intelligent. Also, artificial intelligence may be defined as a collection of analytic tools that attempts to imitate life. Moreover, Researchers are trying to create systems that can mimic human thoughts. AI is used in areas such as credit card fraud detection, medical diagnosis, bank loan approval, financial portfolio management, self-driving cars, and many more. AI technology has three main categories; artificial neural networks, fuzzy logic and evolutionary programming. In the oil and gas industry these tools have been used to solve problems related to pressure transient analysis, drilling, reservoir characterization, and well log interpretation (Mohaghegh, Shale Analytics, 2017).

In artificial intelligence-based reservoir simulation and modeling, we try to mimic or recognise the pattern in the data. Instead of using physics in its first principle and explicit form, we use physics (our scientific understanding of the fluid flow through porous media) as inspiration for building a library of clever observations. In the case of AI-Based Reservoir Models, this library of clever observations is called a customized spatio-temporal database. The spatio-temporal database is used to developing (train) a predictive model by modifying the free parameters that represent the strength of interconnections between parameters. As the training process continues, the algorithm converges to a state where it can mimic the behavior of the hydrocarbon reservoir. In other words, instead of explicitly formulating the physics, we try to deduce the physics from the observations in an implicit fashion.

Artificial intelligence-based reservoir modelling is a young technology and it has been around for only a few years. The potential of this technology is tremendous because reservoir models can be generated in a fraction of the time and budget of traditional models while providing most of the capabilities that the traditional numerical model can provide.

2.1.3 Artificial Neural Network

Artificial neural network is classified to be one of the AI technologies. It can be defined as a system of information processing that perform similar to biological nervous systems. As shown in Figure 1 the output from other neurons is multiplied by the weight of the connection and enters the neuron as input. Usually in a typical neural network has many inputs and only one output. The inputs are summed and subsequently applied to the activation function and the result is the output of the neuron. (Shahkarami, A., Mohaghegh, S. D., Gholami, V., & Haghighat, S. A., 2014, April)

Figure 1: Schematic of Artificial Neuron

(Mohaghegh, Shale Analytics, 2017)

An artificial neural network is a group of neurons that are arranged in particular formations. These neurons have a multilayer network structure (Figure 2). The first layer is the input layer where the number of neurons in this layer are similar to the number of attributes that are being presented to the network as input.

The second layer which is also known as a hidden layer where the neurons in this layer are responsible for modifying the data throughout the system (feature extraction). While, the last layer is the output layer where the number of neurons in this layer could be similar to the number of attributes that are being presented to the network.

Figure 2: Example of Artificial Neural Network

2.2 THE SPATIO-TEMPORAL DATA BASE

Spatio-temporal database is considered to be the backbone of the top-down reservoir model. It is intended to provide the means of integrating all the field measurements (available data) into the empirical model. In order to present the spatio-temporal database to machine learning and pattern-recognition algorithms, the shape of the database has to be flat or a matrix of rows and columns. The rows in the matrix are referenced as a record, while the columns in the matrix are referenced as attributes or parameters. The main two data types that included in spatio-temporal database are static data and dynamic data. Figure 3 shows an example of Spatio-temporal database. The data that includes in spatio-temporal database can be summerized in table 1.

[illegible]

Figure 3: Example of spatio-temporal database

Table 1: Example of the data that included in the Spatio-Temporal Database

Well Location	Well Construction	Well Completion	Formation Evaluation	Well Logs
1) Latitude 2) Longitude 3) TVD 4) MD	1) Vertical 2) Horizontal 3) Slanted 4) Azimuth/ Inclination	1) Open Hole 2) Cased Hole	1) Formation top 2) Gross thickness 3) Porosity 4) Saturation	1) Gamma Ray 2) Density 3) Resistivity 4) Sonic
Core Analysis	Well Interventions	Production/Injection	Operational Constrains	Well Test
1) Permeability 2) Relative Permeability	1) Workovers 2) Stimulation 3) Hydraulic Fracturing	1) Oil 2) Gas 3) Water	1) Shut-in durations 2) Chock size 3) WHP	1) Reservoir Pressure

2.2.1 Static Data

Static data can be defined as the attributes that will not change with time. This data is used to build the geo- cellular model where the oil and gas reside prior production. It is known as a geological or static model. All reservoir rocks are heterogeneous and anisotropic. Static data can be divided into two separate categories. The first category is the truly static data and the second category is the dynamically-modified static data. The truly static data is the parameters that are not expected to change with time for instance the average porosity related with the drainage area (where each well is producing from) is not actually a fixed parameter. While the dynamically-modified static data is the parameters that are expected to change with time. As new wells are drilled in the reservoir, the drainage area that is attainable to each well change with time. The average values of the static attributes that represent the drainage volume, for instance the average porosity related with the drainage area will be subject to alteration. (Mohaghegh, Data-Driven Reservoir Modeling, 2017)

2.2.2 Dynamic Data

Dynamic data can be defined as the attributes that can change with time. Most of the dynamic data represent human intervention in production. This intervention could be intentional or unintentional. Stimulating the well or changing the chock size are example of intentional and changes in well head pressure due to the surface facility limitations is an example of unintentional. Therefore, it is very important to let the top-down model to learn about the differences between the human intervention and reservoir behavior. These differences need to be communicated to the top-down model and the only way to communicate such information is through data. TDM will only be able to differentiate between the two sets of characteristics, and de-convolve the related signals, by learning through historical data, that there is a difference between signals coming from the reservoir and those that have been impacted by the operational constraints.

2.3 TOP-DOWN MODEL

Shahab Mohaghegh is one of the pioneers in applying AI in petroleum engineering. In the recent years he introduced a new technology called a Top-Down Modeling (TDM), which is considered to be the first comprehensive data-driven reservoir modeling developed by him. Top-Down Modeling (TDM) is a pioneering technology that integrates a large number of disciplines such as reservoir modeling, reservoir engineering, advanced data-driven and statistical analysis using machine learning and artificial intelligence. TDM was developed as an alternative to the traditional numerical reservoir simulation in order to build a comprehensive, cohesive and full field reservoir model. (Mohaghegh, S. D., Al-Mehairi, Y., Gaskari, R., Maysami, M., & Khazaeni, Y., October, 2014). The distinguishing features of this technology that recognizes it from the traditional reservoir simulation are as follow;

- It does not assume that we have all the information necessary to build a fully representative geological model of the asset, understanding all the underlying geological behaviour.
- It does not assume that we fully understand and are able to formulate (using physics) all the complexities and intricacies (nuances) of fluid flow through porous media for the asset being modeled.

2.3.1 Top-Down Model – Case Studies

Several papers have been published in recent years that present the applicability data-driven reservoir modeling (Gomez, Y., Khazaeni, Y., Mohaghegh, S. D., & Gaskari, R., 2009, January), also known as Top-Down Modeling (TDM) in developing reservoir simulation models for many different types of reservoirs.

2.3.1.1 TDM for Niobrara Field

TDM was built for a field in Weld County, Colorado, producing from Niobrara (Shahab D. Mohaghegh, S. Alireza Haghighat, Vida Gholami & David Moreno,, April 2014). The Data was collected from more than 145 wells in order to develop a TDM for this field and perform data driven analysis.

This data included production history, well logs, well design attributes, and dynamic production constrains. The workflow for this study included generating a geological model and reservoir delineation followed by Key Performance Indicator (KPI) analysis, and finally history matching the production data from each well and production forecasting. Figure 4 shows the list of inputs (data) for development TDM for Niobrara field.

Top-Down Model Inputs		
Static Data(reservoir properties)	Static Data(well design parameters)	Dynamic Data
Pay Thickness	Well Location	Time
Porosity	Well Drainage Area	No. of Days of Production
Water Saturation	TVD	q-Oil (t-1)
Porosity (offset well)	Perforation Thickness	q-Oil (t-2)
Neutron Porosity (log)	Volume of Total Injected Fluid	Stimulation Date
Formation Top	Weight of Injected Proppant	
	Distance to Offset Well	
	Well Drainage Area (offset well)	

Figure 4: List of inputs (data) for development TDM for Niobrara field

Once the comprehensive data set is generated, Key Performance Indicator (KPI) analysis was made to define the degree of influence of each static or dynamic parameter on the production. Figure 5 demonstrates the KPI analysis result for Niobrara field.

Rank	Feature	% Degree of Influence
1	Stimulation date	100
2	q(t-1)-Oil	93
3	q(t-2)-Oil	79
4	Perf Thickness	60
5	Weight of Inj Proppant	55
6	Porosity (%) (1P)	49
7	X/Longitude	48
8	Porh(1-sw)(1P)	46
9	Porh(1-sw)-Ave.(1P)	46
10	Water Saturation (%)	46
11	Elevation	42
12	Vol of Total Inj Fluid	42
13	Porh(1-sw)-Ave.	40
14	Time	40
15	Resistivity	38
16	Porosity (%)	37
17	Porosity (%) -Ave.	37
18	Top (ft)	37
19	Distance(1P)	36
20	Days of Production(t)	33
21	Top (ft)(1P)	33
22	Y/Latitude	32

Figure 5: KPI analysis result

Once the KPI analysis was performed, the development of TDM using the production data from 145 wells that started in 1986 and continued to December 2012 were used in neural network training. Figure 6 illustrates a good history match results for the entire field and individual wells. Also, the future productions of the wells were predicted for three years starting from year 2013.

Figure 6: TDM estimations for production history and three years prediction from 2013 for (a) Entire field (b, c, d) Different wells

2.3.1.2 TDM for Powder River Basin

This study was performed on Hilight Field in the Powder River Basin, Wyoming. (Maysami, M., Gaskari, R., & Mohaghegh, S. D. , 2013, September) The production data was collected from 185 wells started from June 1969 and extended until April 2012. Figure 7 shows the available data that were used in this analysis are well coordinates, top depth, pay thickness, porosity and completion data. However, the only dynamic data that is available beside the production history is dates and types of workovers on individual wells. Figure 8 and 9 illustrate a good history match results for the entire field and individual wells, respectively. Also, the future productions of the wells were predicted from 2013 through 2017. Gray dots and shades represent annual production history and actual cumulative production in Hilight field, respectively. The green line represents the matching result obtained from TDM model developed.

Top-Down Model Inputs	
Static Data	Dynamic Data
Location - X	Q-Oil (t-1)
Location - Y	Q-Gas (t-1)
Depth	Workover (t-1) Date
Pay Thickness	Workover (t-1) Type
Completion	
Porosity	

Figure 7: List of inputs (data) for development TDM for Powder River Basin

Figure 8: TDM estimations for production history and four years prediction from 2013 for the entire field

Figure 9: TDM estimations for production history and four years prediction from 2013 for different wells

CHAPTER III

METHODOLOGY

3.1 Introduction

In order to accomplish the objectives of this thesis, IMAge software was used for the development of the Top-Down Model using synthetic data. The research strategy for developing the TDM is briefly explained in this chapter. The numerical reservoir simulation model that will be used to generate the data (synthetic data) from has 53 producers and 20 injectors. In addition, it has six reservoir layers. The production started in January 1995 and continued to December 2016. The production timeline consists of seven phases and each phase started at different time and can be illustrated in Figure 10. Furthermore, water injection data was available from 1995 to 2016 and the timeline can be shown in Figure 11.

Figure 10: Production Timeline

	Date																					
Name	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Inj-001																						
Inj-002																						
Inj-003																						
Inj-004																						
Inj-005																						
Inj-006																						
Inj-007																						
Inj-008																						
Inj-009																						
Inj-010																						
Inj-011																						
Inj-012																						
Inj-013																						
Inj-014																						
Inj-015																						
Inj-016																						
Inj-017																						
Inj-018																						
Inj-019																						
Inj-020																						

Figure 11: Water Injection Timeline

3.2 IImagine Software

IMagine is the only software that provides a comprehensive workflow for the development of Top-Down Models (Figure 12). It uses innovative and proprietary algorithms and technologies based on artificial neural networks, genetic optimization and fuzzy logic in order to accomplish its objective. IMagine will be used in this project in order to meet the objectives of the thesis.

Figure 12: IImagine Software

3.3 Research Strategy

The following steps were implemented in order to develop a Top-Down Model.

Figure 13: Research Strategy

1. Modify the Numerical Reservoir Simulation Model

A student at West Virginia University built the numerical reservoir simulation model and the integrity of this model was tested. Then, some modifications were made into the numerical reservoir simulation model. Therefore, the permeability and porosity of layer three and layer five were changed to be zero as shown in Figure 15 and Figure 16 respectively. Also new operational constrains were added to the model, so

Figure 14: Well Location

most of the wells were shut-in for several days and months in order to make the model more realistic. After that, the model was run using CMG software and no errors were found. As mentioned earlier the numerical reservoir simulation model includes 53 producers and 20 injectors. The location of each producer and injector can be illustrated in Figure 14.

Figure 15: Permeability for the six layers

Figure 16: Porosity for the six layers

2. Generate the required data for the Top-Down-Model

After running the numerical reservoir simulation model, only the required data for TDM were exported. The synthetic data was generated (exported) as a layer-based from January 1995 to December 2016. Therefore, upscaling method (Figure 17) was used for all the static and dynamic attributes. Then the upscaled data (well-based data) was used for developing the TDM in order to confirm its capabilities in forecasting existing well behavior. The data generated is classified into static data and dynamic data. The static data contains of well location, well type, grid top, true-vertical-depth, average initial water saturation, average permeability, total thickness and total completion (Figure 18). While the dynamic data includes the well production data (Oil, Gas and Water) average flowing bottom hole pressure, average reservoir pressure, average water saturation and average oil saturation for 53 producers in a monthly basis from 1/31/1995 to 31/12/2016 and can be seen in Figure 19. It also includes the days of production as shown in figure 20.

Static Data	Well Name	Upscaling Method
	well type	N/A
	X-Loc	N/A
	Y-Loc	N/A
	Top	N/A
	TVD	N/A
	Initail Sw	Average
	h	Summation
	k	Average
	Porosity	Average
	Completion	Summation
Dynamic Data	Oil Production	Summation
	Gas Production	Summation
	Water Production	Summation
	FBHP	Average
	Reservoir Pressure	Average
	Water Saturation	Average
	Oil Saturation	Average
	Days of Production	Summation

Figure 17: Upscaling method

Well Name	Well Type	X-Loc	Y-Loc	Top	TYD	Average Swi	Total h	Average k	Average Por	Total Comp
Well-001	P	20829.25	10610.57	4123.43	4329.741211	0.066666667	206.31	58.58	0.068333333	155.35
Well-002	P	13912.5	10810.77	4023.63	4301.978516	0.066666667	278.35	1.375	0.031666667	209.45
Well-003	P	17901	14414.38	3919.56	4270.762695	0.066666667	351.2	13.45666667	0.078333333	243.64
Well-004	P	13425.75	16616.57	4148.46	4418.844238	0.066666667	270.4	24.55333333	0.055	197.87
Well-005	P	20774	17567.53	4095.8	4255.735352	0.066666667	159.93	12.76	0.058333333	127.35
Well-006	P	12486.5	17467.43	4209.49	4412.863281	0.066666667	203.38	315.235	0.098333333	147.81
Well-007	P	11436.75	12412.38	4165.89	4521.438965	0.066666667	355.54	158.3916667	0.085	244.85
Well-008	P	12155	18868.83	4271.89	4346.865723	0.066666667	74.97	5.318333333	0.021666667	61.69
Well-009	P	13536.25	18418.38	4229.81	4347.341797	0.066666667	117.52	65.31166667	0.06	92.44
Well-010	P	21050.25	14264.23	4098.36	4305.600098	0.066666667	207.24	20.55833333	0.06	160.3
Well-011	P	12265.5	13063.02	4147.67	4525.955566	0.066666667	378.29	177.98	0.088333333	262.53
Well-012	P	13315.25	19619.58	4286.31	4346.079102	0.073333333	59.78	132.0183333	0.078333333	50.65
Well-013	P	13912.5	15215.17	4109.26	4457.023438	0.066666667	347.77	50.98833333	0.066666667	245.05
Well-014	P	21160.75	15715.68	4053.9	4267.547852	0.066666667	213.65	17.21833333	0.066666667	156.79
Well-015	P	19890	19719.68	4158.46	4320.705566	0.066666667	162.24	2.823333333	0.026666667	131.53
Well-016	P	11823.5	16566.52	4196.34	4454.918945	0.066666667	258.58	103.6783333	0.075	184.89
Well-017	P	16851.25	16666.63	4004.33	4294.48877	0.066666667	290.14	91.59166667	0.08	207.55
Well-018	P	11657.75	18068.03	4242.67	4382.793945	0.066666667	140.14	80.735	0.06	105.8
Well-019	P	11934	11461.43	4118.63	4450.825684	0.066666667	332.19	20.465	0.066666667	235.65
Well-020	P	11547.25	13713.68	4194.25	4588.25293	0.366666667	394	6.253333333	0.046666667	266.47
Well-021	P	12265.5	15715.68	4178.06	4520.924805	0.066666667	342.87	21.72166667	0.066666667	238.45
Well-022	P	12320.75	10410.38	4072.71	4358.009766	0.073333333	285.31	0.891666667	0.021666667	213.33
Well-023	P	15083.25	14214.18	4059.58	4350.875488	0.066666667	291.31	3.406666667	0.03	218.48
Well-024	P	14420.25	12912.88	4076.38	4383.918945	0.066666667	307.54	8.456666667	0.053333333	227.48
Well-025	P	15249	11711.68	3978.7	4313.311523	0.066666667	334.61	10.905	0.066666667	240.72
Well-026	P	16851.25	19619.58	3898.57	4275.480957	0.066666667	376.92	41.46	0.073333333	257.08
Well-027	P	16298.75	10660.63	3900.99	4272.945313	0.066666667	371.96	22.42333333	0.071666667	247.76
Well-028	P	17790.5	10860.83	3946.28	4269.383789	0.066666667	323.1	25.46333333	0.091666667	228.82
Well-029	P	18343	12212.18	3969.65	4273.86084	0.066666667	304.22	9.071666667	0.071666667	218.84
Well-030	P	19282.25	11111.07	4008.02	4290.356934	0.066666667	282.33	31.49166667	0.088333333	215.94
Well-031	P	19834.75	12112.07	4052.89	4303.44043	0.066666667	250.55	18.02166667	0.063333333	192.26
Well-032	P	20718.75	11161.12	4118.89	4337.911133	0.066666667	219.01	67.23166667	0.083333333	164.07
Well-033	P	21160.75	12112.07	4152.26	4337.445801	0.066666667	185.18	25.63666667	0.055	138.58
Well-034	P	17569.5	12912.88	3919.78	4269.735252	0.066666667	349.97	40.98	0.09	242.3
Well-035	P	21271.25	18918.88	4135.81	4288.618164	0.066666667	152.81	3.735	0.046666667	127.82
Well-036	P	19724.25	18718.68	4100.81	4287.620606	0.066666667	156.82	4.941666667	0.035	128.43
Well-037	P	13646.75	14114.08	4120.53	4480.970703	0.066666667	360.46	110.14	0.076666667	253.22
Well-038	P	18398.25	16766.73	3965.57	4277.134766	0.066666667	311.58	8.975	0.053333333	218.77
Well-039	P	18453.5	18168.13	4062.66	4258.981445	0.066666667	196.32	12.18	0.05	148.65
Well-040	P	20553	13263.22	4108.25	4328.149902	0.066666667	219.91	9.266666667	0.046666667	165.8
Well-041	P	19171.75	13313.28	4024.76	4281.693848	0.066666667	256.92	14.49333333	0.073333333	194.36
Well-042	P	19613.75	17016.98	4044.97	4267.566895	0.066666667	222.61	46.08833333	0.071666667	169.15
Well-043	P	19890	14464.42	4039.05	4294.96582	0.066666667	255.92	11.05	0.068333333	196.18
Well-044	P	19669	15765.73	3984.66	4277.643066	0.066666667	292.99	9.205	0.056666667	211.55
Well-046	P	15746.25	19018.98	4189.91	4338.42627	0.066666667	148.52	31.91333333	0.036666667	114.29
Well-047	P	17845.75	15615.58	3913.5	4277.880371	0.066666667	364.4	51.42666667	0.06	250.41
Well-049	P	14862.25	16066.03	4089.14	4373.851563	0.066666667	284.72	3.845	0.036666667	211.77
Well-051	P	19006	15115.07	3952.62	4273.938965	0.066666667	321.3	5.085	0.053333333	228.46
Well-053	P	13923	12011.98	4077.76	4380.805176	0.066666667	303.05	9.286666667	0.046666667	224.91
Well-054	P	15359.5	16916.88	4103.11	4371.564941	0.066666667	268.45	14.705	0.046666667	198.83
Well-055	P	16077.75	15615.58	4008.86	4297.27002	0.066666667	288.42	43.58333333	0.068333333	210.8
Well-056	P	16575	14264.23	3937.44	4288.834473	0.066666667	351.4	22.49333333	0.085	247.86
Well-057	P	15912	13012.98	3984.05	4291.50293	0.066666667	307.44	4.568333333	0.056666667	224.51
Injector-001	I	10221.25	17517.48	4215.07	4404.933106	0.666666667	189.86	66.66666667	0.043333333	140.47
Injector-002	I	9945	12462.43	4182.66	4536.637695	0.666666667	353.97	66.66666667	0.043333333	242.28
Injector-003	I	10497.5	19619.58	4322.04	4360.979981	0.666666667	38.93	66.66666667	0.043333333	36.08
Injector-004	I	20221.5	9459.43	4007.95	4274.199219	0.666666667	266.24	66.66666667	0.043333333	203.76
Injector-005	I	22652.5	18568.53	4146.9	4311.834961	0.666666667	164.94	66.66666667	0.043333333	133.2
Injector-006	I	14365	20820.78	4258.81	4342.679688	0.666666667	83.87	66.66666667	0.043333333	68.48
Injector-007	I	13923	9309.27	3980.75	4272.998535	0.666666667	292.25	66.66666667	0.043333333	207.79
Injector-008	I	23205	14864.83	4113.57	4287.615723	0.666666667	174.06	66.66666667	0.043333333	137.69
Injector-009	I	17459	9759.73	3911.88	4260.341797	0.366666667	348.47	66.66666667	0.043333333	235.74
Injector-010	I	18177.25	20570.52	4198.42	4348.562012	0.666666667	150.13	66.66666667	0.043333333	115.95
Injector-011	I	22763	11161.12	4222.29	4357.049316	0.666666667	134.77	66.66666667	0.043333333	99.25
Injector-012	I	21658	20370.33	4210.39	4352.521484	0.5	142.12	66.66666667	0.043333333	114.69
Injector-013	I	22431.5	13012.98	4186.36	4343.843262	0.44	157.49	66.66666667	0.043333333	117.83
Injector-014	I	10718.5	14864.83	4176.88	4516.955078	0.496666667	340.07	66.66666667	0.043333333	233.74
Injector-015	I	10497.5	10510.48	4122.34	4445.80957	0.666666667	323.46	66.66666667	0.043333333	231.02
Injector-016	I	22431.5	16966.93	4109.66	4265.019531	0.44	155.36	66.66666667	0.043333333	121.98
Injector-017	I	12486.5	20370.33	4312.31	4359.291016	0.493333333	47	66.66666667	0.043333333	39.53
Injector-018	I	11989.25	9559.53	4078.52	4359.869141	0.666666667	281.37	66.66666667	0.043333333	210.39
Injector-019	I	16077.75	8808.78	3899.72	4259.931152	0.666666667	360.22	66.66666667	0.043333333	237.7
Injector-020	I	16409.25	20270.23	4217.18	4341.55957	0.366666667	124.39	66.66666667	0.043333333	95.17

Figure 18: Static Data

Well Name	Date (month)	Average FBHP	Well Oil Prod. (bbls)	Well Gas Prod. (scf)	Well Water Prod. (bbls)	Average Pressure	Average Sw	Average So
Well-001	1/31/1995	3342.351736	0	0	0	3342.351736	0.06652293	0.600143737
Well-001	2/28/1995	2108.782009	701133.6875	292672096	0.136530116	2585.924805	0.066891817	0.59977485
Well-001	3/31/1995	2085.913488	679416.75	283606848	2014.054199	2522.946541	0.089479208	0.577187459
Well-001	4/30/1995	2136.738883	502774.0313	209871440	31806.01563	2721.115755	0.119262127	0.54740454
Well-001	5/31/1995	2118.808338	453759.1563	189411312	65220.92969	2809.369448	0.141206523	0.525460144
Well-001	6/30/1995	2083.940405	330480.8125	137951600	102204.5469	2822.27251	0.155329031	0.511337635
Well-001	7/31/1995	1856.713111	343542.1563	143403760	145666.7969	2711.091687	0.16421502	0.502451647
Well-001	8/31/1995	2239.092273	234933.9531	98067776	132748.0625	2896.093167	0.174314982	0.492351685
Well-001	9/30/1995	2211.151847	222312.7344	92799336	148000.0781	2910.909473	0.17440624	0.492260426
Well-001	10/31/1995	2195.267015	217813.2344	90921112	162621.0469	2897.924427	0.179519348	0.487147319
Well-001	11/30/1995	1986.418441	230887.0781	96378496	188443.8125	2794.711043	0.183816457	0.48285021
Well-001	12/31/1995	2029.879828	217258.2188	90689440	199377.9063	2813.889373	0.188697031	0.477969635
Well-001	1/31/1996	1974.958102	214860.8438	89688704	215884.2031	2791.223759	0.188128522	0.478538144
Well-001	2/29/1996	3657.741068	0	0	0	3657.741068	0.236278025	0.430388642
Well-001	3/31/1996	2185.166228	166565.8438	69529072	233454.7031	2951.287456	0.193235816	0.473430851
Well-001	4/30/1996	1884.743689	198828.3438	82996312	239446.9688	2755.542733	0.197671672	0.468994995
Well-001	5/31/1996	2212.458555	155325.5156	64837056	210828.1875	2912.130025	0.19740553	0.469261137
Well-001	6/30/1996	3704.622103	0	0	0	3704.622103	0.240907953	0.425758713
Well-001	7/31/1996	3852.128355	0	0	0	3852.128355	0.248224683	0.418441984
Well-001	8/31/1996	2190.746826	133787.4531	55846492	274317.9063	2967.119834	0.203978763	0.462687903
Well-001	9/30/1996	2121.935889	147326.4688	61498044	239908.8125	2894.833171	0.203733361	0.462933306
Well-001	10/31/1996	2101.691706	147404.0781	61530432	248331.4063	2862.859241	0.205521135	0.461145531
Well-001	11/30/1996	2174.59115	131375.6406	54839736	233560.2656	2898.254093	0.207806646	0.458860021
Well-001	12/31/1996	2106.464253	139739.7344	58331128	256343.7813	2866.176222	0.208977041	0.457689626

Figure 19: Dynamic Data

Well Name	7/31/2002	8/31/2002	9/30/2002	10/31/2002	11/30/2002	12/31/2002	1/31/2003	2/28/2003	3/31/2003	4/30/2003	5/31/2003	6/30/2003	7/31/2003	8/31/2003	9/30/2003	10/31/2003	11/30/2003	12/31/2003	1/31/2004
Well-001	19	22		24	21	23	25	22	21	20	23	22		21	20	26	19		23
Well-002	23				21	22		16	26	22	22	24	28	24	24	27	21		22
Well-003		23	22	24	23	24	21	20	21	23			22	24		22	23	28	
Well-004	24	26		26	21	24	20	21			24	24		23		23	25	22	18
Well-005	18		19	24	23	22	24	25	27	23	25	22	21	26	19		23	20	21
Well-006	21	27	20		24	23		20	25	24	27		25	22	22	27	25	22	20
Well-007	20		25	22		24	26	22	24	18	22		23	25	23	25	25	23	20
Well-008	23	21		23	21	21		22	22	27	23	22		26		25	23	25	23
Well-009		25	24	24	19	22	25		25	24	20	21	26		25	21	23		
Well-010	26	22	20	24	24		20	21	25	23	24	20	22	25	23	22	21	26	26
Well-011	23	29	20		22	17	20	21		21	22	22	25	27	23			24	
Well-012	23		20	21	22	22	24	20	24	24	21		19			24			25
Well-013	19	22	24	26	18	22		24	26	24	24	28	19	27					29
Well-014	26		21	22		26		24	25	24	22	21	24	20	24	20	19	19	25
Well-015		25	21			26	26	21	27	25	22	23	22			24		21	24
Well-016	18	24	23	27	19	23		19	23		26	18	22	21	27				26
Well-017	24			21	22	23	25	20	21	24		23		22	26	25		22	
Well-018	23	22	20	24	24		24		22	20	20	19	21		24	23	22		22
Well-019	19	17	25		22		27	19	25	26	28	23	20		20		22	24	22
Well-020	23	22	24		23	24	24	23	25	22	22		23	27	23	24	25		26
Well-021		25	25		24	21	23	24	20	23	28		20	25	21		22		25
Well-022	24	22		21		21	20	22	25		24			26	20	20		24	27
Well-023	24		22	21	27	25	23	25	25		22	23	30	18	25	23	20		25
Well-024	20	26	19	23	23	26		21	22	24	22	23	19	25	24	21	22	23	
Well-025	24	21		22	21		21	19	25	23	28	23	23	25		25		24	25
Well-026	21	18		24	25		24	22	20	23	21	21	26	23	20	25	24	20	24
Well-027	25	23		24	25	22	27		22	26		22	21	23	22		26	23	19
Well-028	25		22	23	25	27	23	21	23		24	18	22		23	20	22		25
Well-029	24	25		19	18	21	22	18		21	25	21	23		22	25	23	24	27
Well-030		20	20	27		21	26	22			24	24	24	26	19		20	25	24
Well-031	24	21		21		23		21		22	24	21	23	22		21	20	19	25
Well-032	18	19	26	25	20	19	27	20		22	22	25	25		24	23		17	24
Well-033	27	24	23	22		22	22		27		21	18	21	18		22	25	24	23

Figure 20: Days of Production

3. Importing data into IImagine software

After generating the data from numerical reservoir simulation, then the data was imported into IImagine software. As shown in Figure 21 the static and dynamic datasets were imported into “Well-Based Data” and oil, gas, and water production datasets were imported into “Production Rate Data”. The dynamic and production rate data from 01/31/1995 to 12/31/2014 were only imported into IImagine software and the last two years were not introduced into the software at all in order to test the TDM predictions with the result of numerical reservoir simulation data. The timelines used for modeling and history matching of the top-down model, blind history matching, and forecasting are shown in Figure 22

Figure 21: Importing the data

Figure 22: History Matching strategy

4. Static Modeling

In this section static modeling that includes grid and boundary, geo-statistics, reservoir delineation and volumetric were performed before proceeding to the Top-Down Modeling section. Reservoir grid size and reservoir boundary were manually adjusted as shown in Figure 23. In geo-statistics section, the models for both static and dynamic attributes were created with the application of inverse distance weighing method. Moreover, the reservoir delineation that includes the drainage area calculations were performed by using the Voronoi technique delineation of the created boundary. Lastly, the volumetric calculations were generated.

Figure 23: Reservoir Boundary

5. Top-Down Modeling: (Model Training and History Matching)

Build and History match section includes three steps as shown in Figure 24. The first step is the design and status where the model (output) is created, then the second step is the attribute selection and the last step is to generate a comprehensive dataset, which is also known as a Spatio-Temporal database. In Build and History match section the outputs (reservoir pressure, water saturation, oil production, gas production, and water production) were modeled using different attributes. Figure 25 shows the sequences of the outputs (Top-Down Models) that were modeled. In this figure, the static data from the spatio-temporal database along with dynamic data (mainly operational constraints) from the spatio-temporal database at time (t) are needed (as well as the “Reservoir Pressure” at time $t - 1$) to generate the “Reservoir Pressure” at time (t) for all the wells in the asset. Next, static data along with dynamic data at time (t) (mainly operational constraints), as well as recently calculated reservoir pressure at time (t), are required as input to the data-driven water saturation model (as well as the water saturation at time $t - 1$) in order to calculate water saturation at time (t) for all the wells in the asset. Similarly, to calculate the production rates (Oil $\rightarrow$ Gas $\rightarrow$ Water) at each well at time (t), static data along with dynamic data from time (t) as well as recently calculated reservoir pressure and water saturation at time (t) (along with production rates from time $t - 1$) are required to be used in the data-driven production rate model.

The screenshot shows the 'Build and History Match' software interface. It has three tabs: 'Design & Status 1', 'Attribute Selection 2', and 'Comprehensive Dataset 3'. The 'Design & Status' tab is active.

Model Information:

- Model Name:
- Model Output:
- Time Resolution: ☐ Daily ☒ Monthly ☐ Yearly

Closest Offset Wells:

- Number of Offset Wells (Producer):
- Number of Offset Wells (Injector):
- ☒ Do not select any offset wells without value.
- ☐ Use offset well(s) from the same layers

Model Date Range:

- ☐ Use history matched results for missing values.
- ☐ Use other auxiliary data sources for missing values.
- Development Start:
- Development End:
- Deployment Start:
- Deployment End:

Add Data-Driven Model

Data-Driven Models Table:

Model Name	Model Output	Model Status	Delete
gas	q(t)-Gas	Completed (Click to Open)	☐
oil	q(t)-Oil	Completed (Click to Open)	☐
Pr	Reservoir Pressure (psi)(t)	Completed (Click to Open)	☐
Sw	Water Saturation (%) (t)	Completed (Click to Open)	☐
water	q(t)-Water	Completed (Click to Open)	☐

Refresh Model List

Hold down "Shift" key while clicking on any model status to regenerate the dataset.

Figure 24: Build and History Match

Figure 25: Sequences of Top-Down Models (Output) design

Before creating the spatio-temporal database, different attributes were selected for each output in order to perform the Top-Down Modeling as shown in Figure 26. The green symbol means the attribute has been selected for TDM development and the red symbol means the attribute has not been selected for TDM development. Only the data (dynamic and static data) for two offset producers and one offset injector along with the focal data were used in building the TDM. Once the attributes are selected, the Spatio-Temporal database was created for the five models.

Item	Data	Parameters	Model					Item	Data	Parameters	Model					
			Pr (t)	Sw (t)	Oil (t)	Gas (t)	Water (t)				Pr (t)	Sw (t)	Oil (t)	Gas (t)	Water (t)	
Focal Attributes (Producers)	Well Location	Time	✓	✓	✓	✓	✓	Offset Attributes (Producers)	Well Location	Time	✓	✓	✓	✓	✓	
		XLongitude	✓	✓	✓	✓	✓			Static Data	Distance (ft)	✓	✓	✓	✓	✓
		YLatitude	✓	✓	✓	✓	✓				Initial Sw %	✗	✗	✗	✗	✗
	Drainage Area	✓	✓	✓	✓	✓	Completion (ft)		✗		✗	✓	✗	✗		
	Static Data	Initial Sw %	✓	✓	✓	✓	✓		Pay Thickness		✓	✓	✓	✓	✓	
		Completion (ft)	✓	✓	✓	✓	✓		Porosity %		✓	✓	✓	✓	✓	
		Pay Thickness	✓	✓	✓	✓	✓		Permeability md		✓	✓	✓	✓	✓	
		Porosity %	✓	✓	✓	✓	✓		Porh(1-Sw)		✗	✗	✗	✗	✗	
		Permeability md	✓	✓	✓	✓	✓		TVD (ft)	✓	✓	✓	✓	✓		
		Porh(1-Sw)	✓	✓	✓	✓	✓		Top (ft)	✗	✗	✓	✗	✗		
		TVD (ft)	✓	✓	✓	✓	✓		Dynamic Data	FBH Pressure (psi) (t)	✓	✓	✓	✓	✓	
	Top (ft)	✓	✓	✓	✓	✓	FBH Pressure (psi) (t-1)			✓	✓	✓	✓	✓		
	Dynamic Data	FBH Pressure (psi) (t)	✓	✓	✓	✓	✓			Days of Production (Day) (t)	✓	✓	✓	✓	✓	
		FBH Pressure (psi) (t-1)	✓	✓	✓	✓	✓			Days of Production (Day) (t-1)	✓	✓	✓	✓	✓	
		Days of Production (Day) (t)	✓	✓	✓	✓	✓			Reservoir Pressure (psi) (t)	✗	✗	✗	✗	✗	
		Days of Production (Day) (t-1)	✓	✓	✓	✓	✓			Reservoir Pressure (psi) (t-1)	✓	✓	✓	✓	✓	
		Reservoir Pressure (psi) (t)	✓	✓	✓	✓	✓			Water Saturation % (t)	✗	✗	✗	✗	✗	
		Reservoir Pressure (psi) (t-1)	✓	✓	✓	✓	✓	Water Saturation % (t-1)	✓	✓	✓	✓	✓			
		Water Saturation % (t)	✗	✓	✓	✓	✓	q(t) Oil	✗	✗	✗	✗	✗			
	Rate	Water Saturation % (t-1)	✓	✓	✓	✓	✓	q(t-1) Oil	✓	✓	✓	✓	✓			
q(t) Oil		✗	✗	✓	✓	✓	q(t) Gas	✗	✗	✗	✗	✗				
q(t-1) Oil		✓	✓	✓	✓	✓	q(t-1) Gas	✓	✓	✓	✓	✓				
q(t) Gas		✗	✗	✗	✓	✓	q(t) Water	✗	✗	✗	✗	✗				
q(t-1) Gas		✓	✓	✓	✓	✓	q(t-1) Water	✓	✓	✓	✓	✓				
q(t) Water		✗	✗	✗	✗	✓	Offset Attributes (Injectors)	Well Location	Distance	✓	✓	✓	✓	✓		
q(t-1) Water		✓	✓	✓	✓	✓			Dynamic Data	Water Injection (t)	✓	✓	✓	✓	✓	
							Water Injection (t-1)	✓		✓	✓	✓	✓			

Figure 26: The attributes that have been selected for building the TDM

Figure 27 is an example of Spatio-Temporal database that has been created for oil production model. Once the Spatio-Temporal database is created, then data cleaning are performed by removing the zero values of oil production first, followed by assigning zero to the missing values and after that sorting by well and then by date. The number of total cases (records) were 6572 after excluding the oil that has zero production from the Spatio-Temporal dataset. Table 2 shows the number of total cases that has been assigned for training, calibration and validation. In this thesis, the Top-Down modeling was done using resolution in time. Therefore, Multi random portioning method was selected and the last year 2014 that has 509 records were assigned as a blind validation and 85% of the total cases excluding the 509 records were assigned as a training dataset and 15% of the total cases excluding the 509 records were assigned as a calibration dataset. Next, the neural network is trained, calibrated and validated in a satisfactory manner, the results are evaluated against the actual data (data generated by numerical reservoir simulation) in order to see if the top-down model is able to match the production history for all the wells in the field (history matching). The result of the training, calibration and validation will be presented in the next chapter.

Well Information				Offset Wells Producer		Offset Wells Injector			Output
Index	Well Index	Well Name	Time Index	q(t-1)-Oil(2P)	q(t-1)-Water(2P)	Distance(t)(11)	Water injection (bbl)(t-1)(11)	Water injection (bbl)(t-1)(11)	q(t)-Oil
1	2	Well-002	01/31/1995	0	0	1506	371700.375		0 22645.04
2	4	Well-004	01/31/1995	0	0	3226	310988.7813		0 149186.2
3	5	Well-005	01/31/1995	0	0	1763	162175.1563		0 123173.1
4	1	Well-001	02/28/1995	22645.04	0.03	1303	346736.1875	450676.5313	701133.6
5	2	Well-002	02/28/1995	123173.12	0.03	1506	197162.6875	371700.375	27867.38
6	4	Well-004	02/28/1995	123173.12	0	3226	161952.6875	310988.7813	137771.4
7	5	Well-005	02/28/1995	22645.04	0	1763	108354.1016	162175.1563	106596.2
8	1	Well-001	03/31/1995	27867.38	0.02	1303	370666.25	346736.1875	679416.7
10	3	Well-003	03/31/1995	701133.69	0.14	4676	221503.9375	228377.2656	241824.8
11	4	Well-004	03/31/1995	106996.27	0.14	3226	120295.1719	161952.6875	182258.3
12	5	Well-005	03/31/1995	137771.42	0.02	1763	102142.8984	108354.1016	99558.84
13	1	Well-001	04/30/1995	99558.84	0.02	1303	325624.6563	370666.25	502774.0
14	2	Well-002	04/30/1995	192298.34	0.03	1506	133363.5625	166149.6406	26413.54
16	4	Well-004	04/30/1995	99558.84	0.02	3226	85183.64063	120295.1719	205839.9
17	5	Well-005	04/30/1995	679416.75	2014.05	1763	88430.60938	102142.8984	141978.7
18	1	Well-001	05/31/1995	26413.54	0.02	1303	295290.5938	325624.6563	453759.1
19	2	Well-002	05/31/1995	502774.03	31806.02	1506	120840.5391	133353.5625	32376.8
20	3	Well-003	05/31/1995	502774.03	31806.02	4676	182475.2813	194592.2031	231336.7
21	4	Well-004	05/31/1995	141978.75	31806.02	3226	71854	85183.64063	199849.9
22	5	Well-005	05/31/1995	206839.98	0.02	1763	84316.57813	88430.60938	136857.6
23	1	Well-001	06/30/1995	136857.61	0.02	1303	248951.6406	295290.5938	300480.8
24	2	Well-002	06/30/1995	199849.92	0.02	1506	104200.3594	120840.5391	31236.96
25	3	Well-003	06/30/1995	453759.16	65220.93	4676	160393.4844	182475.2813	246015.7
26	4	Well-004	06/30/1995	32376.8	0.02	3226	59283.25391	71854	194727.5

Figure 27: Example of Spatio-Temporal database for Oil

Table 2: Number of cases in training, calibration and validation

Total Cases	Validation (year 2014)	Total cases excluding the last year	Training	Calibration
6572	509	6063	5154	909

6. Forecasting

Once the TDM is developed (trained, calibrated and verified) in a satisfactory manner from 1995 to 2014, then the developed models will be deployed in the forecast mode in order to estimate the future production of oil, gas, and water production and test them against the data that was generated by the numerical reservoir simulation. However, it is very important to add the operational constrains of the years that will be predicted before deployment or forecasting. Therefore, the operational constrains data were added into the TDM deployment section as shown in Figure 28. This data only includes days of production, FBHP and water injection from 01/01/2015 to 12/31/2016. Once the data was updated, then TDM was deployed. The forecasting results will be presented in the next chapter.

The screenshot displays the 'TDM Deployment (TDM-SNR-02)' software window. The interface is divided into two main tabs: 'Deployment Setup' and 'Results'. The 'Deployment Setup' tab is active and contains two steps:

- Step 1: Select a TDM**
 - A table lists available TDMs:
- Step 2: Setup Dates and Options**
 - Includes date selection (1/31/1995 to 12/31/2016), buttons for 'History Match', 'Forecast', 'Reset Dates', 'Update Operational Conditions', 'Add New Wells', 'Deployment Options', and a large 'Deploy TDM' button.

A sidebar on the left contains three buttons: 'Add New Wells', 'Operational Conditions', and 'TDM'.

TDM Name	TDM Output	Resolution	Levels	Start
TDM-Random	q(t)-Water	Monthly	5	1/31
TDM-Random new	q(t)-Water	Monthly	5	1/31
TDM-SNR-01	q(t)-Water	Monthly	5	1/31
TDM-SNR-02	q(t)-Water	Monthly	5	1/31

Index	Input Parameter
1	Days of Production
2	FBH Pressure (psi)
3	Distance
4	Water injection (bbl)

Figure 28: TDM deployment section

CHAPTER IV

RESULT

4.1 Training, Calibration and Validation Results

The results of the developed (trained, calibrated and validated) TDM for reservoir pressure, water saturation, oil production, gas production and water production are illustrated in this section. After multiple of trial and error, the best model was selected based on the obtained R^2 of the three sets (Training, Calibration and Verification). As shown in the Figures 29 and 30, it can be seen that the three sets (Training, Calibration and Verification) for the five models have a pretty good pattern. That means that the TDM is trained, calibrated and validated in a satisfactory manner. Therefore, these models (reservoir pressure, water saturation, oil production, gas production and water production) are used to perform the predictions. The R^2 result for the training, calibration and validation datasets can be summarized in table 3.

Figure 29: Results of training, calibration validation for Reservoir pressure and water saturation

Figure 30: Results of Training, Calibration and Validation for Oil, Gas and Water

Table 3: The R^2 result for Training, Calibration and Validation datasets

Output \ Dataset	Training	Calibration	Validation
Reservoir Pressure	0.988	0.98	0.982
Water Saturation	0.992	0.99	0.993
Oil Production	0.978	0.902	0.821
Gas Production	0.985	0.94	0.831
Water Production	0.986	0.978	0.984

4.2 Top-Down Model Results (History Matching and TDM Predictions)

The results of training and history matching, blind history matching, and forecasting of the top-down model are shown in Figures 31 through 34. Each of these figures includes detailed history matching and forecasting of four individual wells (Well-006, Well-009, Well-021 and Well-037). In each of the figures, three graphs are shown. In all three graphs, the x-axis is time (date) that extends from the initial production date to the forecast time of 2016. The time in the x-axis is divided into three segments identifying the period of time used for training and history matching of the top-down model (1995 to 2013—before the pink line), the period of time used for blind history matching (2013 to 2014—between pink line and olive line), and the period of time used for forecasting (2015 and 2016—after olive line). In each of the graphs in Figures 31 through 34, actual data are shown using green dots, while the results from the top-down model are shown as solid grey lines. In these figures, the graph at the top shows the oil production as a function of time. The middle graph shows the gas production as a function of time. The bottom graph shows water production as a function of time. These figures illustrated a pretty good history matching. Furthermore, it clearly shows that TDM is quite powerful when it comes to history matching past production measurements (actual data) from every individual well in the field. As demonstrated in Shahab's book (Mohaghegh, *Data-Driven Reservoir Modeling*, 2017), the top-down model does this by learning the reservoir and well-production behaviour using the internal correlations that it builds between static and dynamic parameters with production from each well, taking into account production constraints and injection and production from offset wells. This is accomplished one record at a time and then is put together to present production from a well and ultimately production from the entire field, as shown in Figure 35. In this figure the entire reservoir (entire field) is illustrated along with the active wells. The accuracy of the top-down model during the blind history match, as demonstrated in Figures 31 through 35 is an impressive accomplishment, especially when it is compared with results from numerical reservoir simulation. The comparison of TDM result with numerical reservoir simulation result for the four wells will be demonstrated next section. In this section only the result of four wells out of 53 wells are presented. The results of the rest of the wells can be found in the appendix.

Figure 31: Complete History Matching and Prediction result for well-006

Figure 32: Complete History Matching and Prediction result for well-009

Figure 33: Complete History Matching and Prediction result for well-021

Figure 34: Complete History Matching and Prediction result for well-037

Figure 35: Complete History Matching and Prediction results for the entire field (reservoir)

4.3 Confirming Results of TDM Predictions using Numerical Reservoir Simulation data

The objective of this thesis is to confirm the results of Data-Driven Reservoir Modeling which is also known as a Top-Down Modeling (TDM) using the data generated from the Numerical Reservoir Simulation. In this section the result of the TDM predictions (2015 and 2016) are tested against the synthetic data. As mentioned in Chapter 3 “methodology” the data for the last two years (2015 and 2016) that has been generated by numerical reservoir simulation were not introduced to the Data-Driven reservoir modeling software (IMagine). That means the TDM will predict the last two years that has never seen before. Therefore, based on the Artificial Intelligence and Machine Learning and the available data from 1995 to 2014, the last two years were predicted. In order to do the comparison, the results of training and history matching, blind history matching, and forecasting of the top-down model were exported from IMagine software. Then, the results of the TDM were plotted against the results of numerical reservoir simulation using Python as shown in Figures 36 through 39. Each of these figures includes detailed history matching and forecasting of four individual wells (Well-006, Well-009, Well-021 and Well-037). In each of the figures, three graphs are shown. In all three graphs, the x-axis is time (date) that extends from the initial production date to the forecast time of 2016. The time in the x-axis is divided into three segments identifying the period of time used for training and history matching of the top-down model (1995 to 2013—before the pink line), the period of time used for blind history matching (2013 to 2014 - between pink line and olive line), and the period of time used for forecasting (2015 and 2016 - after olive line). In each of the graphs in Figures 31 through 34, actual data are shown using green dots, while the results from the top-down model are shown as solid grey lines. In these figures, the graph at the top shows the oil production as a function of time. The middle graph shows the gas production as a function of time. The bottom graph shows water production as a function of time. Based on the graphs below, the result of the TDM predictions of the last two years (2015 and 2016) for the oil production, gas production and water production has reflected the same result as numerical reservoir simulation. Therefore, we can clearly say data-driven reservoir modeling is a reliable and promising technology and it can be trusted and used with real field measurements data.

Figure 36: TDM result versus numerical reservoir simulation result for well-006

Figure 37: TDM result versus numerical reservoir simulation result for well-009

Figure 38: TDM result versus numerical reservoir simulation result for well-021

Figure 39: TDM result versus numerical reservoir simulation result for well-037

CHAPTER V

CONCLUSION

5.1 Conclusion

In order to efficiently develop and operate a petroleum reservoir, it is important to have a reservoir model. Nowadays, the only technique that is accepted and is being used in our industry is the reservoir numerical simulation. However, this technology is not accurate because it does not use the large amount of the available data from the mature fields. Therefore, data driven reservoir modeling technology, also known as Top-Down Model (TDM), provides a complete alternative to the numerical reservoir simulation model and can serve as an appropriate tool for reservoir management. TDM combines all field measurements into a comprehensive reservoir model to predict the production from each well in a field with multiple wells and then TDM is used to predict the well performance for the future of the field.

There are many opinions, speculations and criticism when we do not use the physics-based approach. Therefore, in this thesis synthetic data generated from a numerical reservoir simulation model was used for the development of a data-driven reservoir modeling to confirm the capabilities of TDM technology.

TDM was developed (trained, calibrated and validated) and history matched using the data generated by a complex numerical reservoir simulation model. The result clearly shows that TDM is quite powerful when it comes to history matching past production measurements (actual data) from every individual well in the field. Furthermore, predictions were made using the developed TDM and are tested against the data that was generated by the numerical reservoir simulation. It has been noticed that the result of the TDM predictions of the last two years (2015 and 2016) for the oil production, gas production and water production has reflected and confirmed to be almost the same result as numerical reservoir simulation. Therefore, we can clearly say data-driven reservoir modeling using artificial intelligence and machine learning is a reliable and promising technology and it can be trusted and used with real field measurements data.

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