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Top-Down Model Development Using Data Generated from a Complex Numerical Reservoir Simulation with Water Injection

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TOP-DOWN MODEL DEVELOPMENT USING DATA GENERATED FROM A COMPLEX NUMERICAL RESERVOIR SIMULATION WITH WATER INJECTION

Yvon Andrea Martinez Gomez

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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ABSTRACT

Top-Down Model Development Using Data Generated from a Complex Numerical Reservoir Simulation with Water Injection

Yvon Martinez

Numerical simulation and data-driven modeling are two current approaches in engineering reservoir modeling. Numerical reservoir simulation attempts to match past production history by modifying reservoir properties of the model. After multiple computationally intensive trial and error efforts, accurate history matches are identified. These history matches are used by project management for production forecasting purposes. Data-driven reservoir modeling utilizes measured data and is, therefore, free of assumptions that are often included in numerical reservoir simulations. Artificial intelligence and machine learning algorithms are technologies implemented in the development of a data-driven reservoir model with efforts to learn fluid flow through porous media from the datasets provided to the system. Training, calibration, and validation datasets ensure the success during the teaching process.

Models, such as oil, gas, and water production, reservoir pressure and water saturation, are trained, calibrated, verified to ensure the success in the teaching process. After appropriate hyperparameter tuning, well-trained models are tested on blind datasets. This leads to the model being deployed on new datasets to again test the model's performance during forecasting. The accuracy is based upon the model achieving a similar result to what numerical simulation found on the same dataset.

The objective of this thesis is to use a 22-year dataset from a reservoir model generated by a numerical simulator that undergoes many complexities to approach the reality that takes place in the industry through the use of operational constraints, workover events requiring shut-in, random bottom hole pressure ("BHP") trend, etc. Should the Top Down Model ("TDM") be able to accurately learn the relationships between input attributes and outputs from the data, a similar procedure can then be applied to real field data in the future. The TDM's capabilities will attempt to be proved when the blind validation's in-time results match the data from the numerical simulation reservoir model. This will be done by excluding the data from the training, calibration,

and validation datasets used to create the TDM. This thesis's results should demonstrate that data-driven modeling is capable of history matching and forecasting the complexities of a reservoir.

Contents

ABSTRACT.....	ii
List of Figures	xi
List of Tables	xxxv
List of Equations	xxxvii
Acknowledgements.....	xxxviii
1 INTRODUCTION.....	1
1.1 Problem statement.....	1
1.2 Thesis Outline	2
2 LITERATURE REVIEW	3
2.1 Numerical Simulation	3
2.2 Machine Learning	4
2.2.1 The Neuron	4
2.2.2 Artificial Neuron – Structure Replication.....	5
2.2.3 Artificial Neural Networks	6
2.2.4 Datasets.....	10
2.2.5 Data Partitioning	11
2.3 Data Mining	12
2.4 Previous Work	14

3	NUMERICAL RESERVOIR MODELING	20
3.1	Original Numerical Reservoir Model	21
3.1.1	Reservoir Model Overview	22
3.1.1.1	General Properties	22
3.1.1.2	Original Map Files	23
3.1.2	Reservoir Characteristics	30
3.1.3	Components	30
3.1.4	Rock Fluid Properties	31
3.1.5	Initial Conditions	31
3.1.6	Numerical Controls	32
3.1.7	Wells and Recurrent	32
3.2	Modified Reservoir Model	33
3.2.1	Merging Layers	33
3.2.2	Geological Restructuring	34
3.2.3	Removing Aquifer Properties	36
3.2.4	Modified Map Files	38
3.2.5	Field Development	46
3.2.6	Operational Constraints	47
3.2.7	Workover Events	47
3.2.8	Partial Completion Strategy:	50
3.3	Available Data	53
4	DATA-DRIVEN RESERVOIR MODELING	57
4.1	Data Preparation	58
4.1.1	Data Formatting	58

4.1.2	Data Collection	60
4.1.2.1	Static Data	60
4.1.2.2	Dynamic Data	62
4.1.3	Data Cleansing	63
4.2	Data Import	65
4.3	Static Modeling	66
4.3.1	Grid and Boundary	66
4.3.2	Geostatistics	67
4.3.3	Reservoir Delineation	68
4.3.4	Volumetric	69
4.4	Top-Down Modeling	70
4.4.1	Build and History Match	71
4.4.1.1	Scenario 1 – Random Partitioning TDM	72
4.4.1.2	Scenario 2 – Mixed Partitioning (1 Year Validation)	78
4.4.1.3	Scenario 3 – Mixed Partitioning (2 Year Validation)	82
4.4.1.4	Scenario 4 – Mixed Partitioning (1 Year Forecast)	87
4.4.1.5	Scenario 5 – Mixed Partitioning (2 Year Forecast)	92
4.4.2	Summary of Conducted Scenarios	97
5	RESULTS AND DISCUSSION	100
5.1	Entire Field:	100
5.2	Well by Well:	114
5.2.1	Individual Production Analysis:	114
5.2.2	Collective Production Analysis:	119

6	CONCLUSIONS	134
6.1	Future Work	135
	APPENDIX.....	140
7	Appendix A: Well Biography.....	140
8	APPENDIX B: Key Performance Indicators.....	169
8.1	Oil Rate	169
8.2	Gas Rate	172
8.3	Water Rate	174
8.4	Reservoir Pressure	176
8.5	Water Saturation	178
9	APPENDIX C: Scenario 1 – Random Partitioning TDM	180
9.1	Input Attributes	180
9.1.1	Oil Predictive Model.....	180
9.1.2	Gas Predictive Model.....	181
9.1.3	Water Predictive Model	182
9.1.4	Reservoir Pressure Predictive Model.....	183
9.1.5	Water Saturation Predictive Model.....	184
9.2	Production Profile Plots	185
9.2.1	Entire Reservoir	185
9.2.2	Good History Match of Production.....	186
9.2.3	Average History Match of Production.....	200
9.2.4	Poor History Match of Production.....	215

9.3	Distribution Maps	216
10	Appendix D: Scenario 2 – Mixed Partitioning TDM (1 Year Validation)	220
10.1	Input Attributes	220
10.1.1	Oil Predictive Model.....	220
10.1.2	Gas Predictive Model.....	221
10.1.3	Water Predictive Model	222
10.1.4	Reservoir Pressure Predictive Model.....	223
10.1.5	Water Saturation Predictive Model.....	224
10.2	Production Profile Plots	225
10.2.1	Entire Reservoir	225
10.2.2	Good History Match of Production.....	226
10.2.3	Average History Match of Production	240
10.2.4	Poor History Match of Production.....	254
10.3	Distribution Maps	256
11	Appendix E: Scenario 3: Mixed Partitioning TDM (2 Year Validation)	260
11.1	Input Attributes	260
11.1.1	Oil Predictive Model.....	260
11.1.2	Gas Predictive Model.....	261
11.1.3	Water Predictive Model	262
11.1.4	Reservoir Pressure Predictive Model.....	263
11.1.5	Water Saturation Predictive Model.....	264
11.2	Production Profile Plots	265
11.2.1	Entire Reservoir	265

11.2.2	Good History Match of Production.....	266
11.2.3	Average History Match of Production.....	277
11.2.4	Poor History Match of Production.....	293
11.3	Distribution Maps	295
12	Appendix F: Scenario 4 – Mixed Partitioning TDM (1 Year Forecast).....	299
12.1	Input Attributes	299
12.1.1	Oil Predictive Model.....	299
12.1.2	Gas Predictive Model.....	300
12.1.3	Water Predictive Model	301
12.1.4	Reservoir Pressure Predictive Model.....	302
12.1.5	Water Saturation Predictive Model.....	303
12.2	Production Profile Plots	304
12.2.1	Entire Reservoir	304
12.2.2	Good History Match of Production.....	305
12.2.3	Average History Match of Production.....	325
12.2.4	Poor History Match of Production.....	334
12.2.5	Good Forecast Production.....	335
12.2.6	Average Forecast Production.....	340
12.2.7	Poor Forecast Production.....	346
12.3	Distributions Maps.....	353
13	Appendix G: Scenario 5 – Mixed Partitioning (2 Year Forecast)	357
13.1	Input Attributes	357
13.1.1	Oil Predictive Model.....	357

13.1.2	Gas Predictive Model.....	358
13.1.3	Water Predictive Model	359
13.1.4	Reservoir Pressure Predictive Model.....	360
13.1.5	Water Saturation Predictive Model.....	361
13.2	Production Profile Plots	362
13.2.1	Entire Reservoir	362
13.2.2	Good History Match Production.....	363
13.2.3	Average History Match of Production.....	378
13.2.4	Poor History Match of Production.....	391
13.2.5	Good Forecast Production.....	392
13.2.6	Average Forecast Production.....	398
13.2.7	Poor Forecast Production.....	408
13.3	Distribution Maps	412

List of Figures

Figure 2-1: Biological Neuron's Structure	5
Figure 2-2: Artificial Neural Network Structure	5
Figure 2-3: Mathematical Representation of a Neural Network.....	7
Figure 2-4: Logistic Sigmoid Activation Function.....	9
Figure 2-5: Tanh Activation Function	9
Figure 2-6: Leaky Relu Activation Function.....	9
Figure 2-7: MISH Activation Function.....	9
Figure 2-8: Data Partitioning Techniques.....	12
Figure 2-9: Data Mining Steps.....	13
Figure 2-10: TDM prediction against historical Production of Well A [20]	15
Figure 2-11: History Match and Forecasting Results for Oil (A), Gas (B) and Water (C) the Entire Reservoir	16
Figure 2-12: Comparison between the predicted and the target flow rate ratio (Q/Q_{max}) using the ANN model for the (A) training and (B) testing datasets [21]	17
Figure 2-13: Neural Network Development Results for Training (A), Calibration (B), Verification (C) and Blind (D) datasets	18
Figure 2-14: Generated output “NN-PHIE” and actual value “PHIE”	19
Figure 3-1: Thesis Workflow	21
Figure 3-2: Grid Block Dimensions.....	22
Figure 3-3: Reservoir Model Overview	22
Figure 3-4: Porosity Map Files for All 6 Layers.....	24
Figure 3-5: Permeability, I (mD) Map Files in All 6 Layers	25
Figure 3-6: Permeability, K (mD) Map Files in All 6 Layers	27

Figure 3-7: Initial Water Saturation Map Files for All 6 Layers	28
Figure 3-8: Grid Thickness (ft) Map Files for all 6 Layers	29
Figure 3-9: Reservoir's Coordinates	30
Figure 3-10: Relative Permeability Curves.....	31
Figure 3-11: Well Locations on Initial Water Saturation Map	32
Figure 3-12: Original Model - 6 Geological Layers	33
Figure 3-13: Thesis Model - 3 Merged Geological Layers.....	33
Figure 3-14: Stratigraphic Trap	34
Figure 3-15: Original Model – Anticline/Syncline Pair	35
Figure 3-16: Thesis Model – Stratigraphic Trap.....	35
Figure 3-17: Thesis Grid Top Map File.....	36
Figure 3-18: Aquifer Boundary Effect.....	37
Figure 3-19: Thesis - Porosity Map Files	39
Figure 3-20: Porosity Distribution – 3 Layers	40
Figure 3-21: Thesis - Permeability, I Map Files	41
Figure 3-22: Permeability (I, J direction) – 3 Layers.....	42
Figure 3-23: Thesis - Permeability, K Map Files	43
Figure 3-24: Permeability (K-direction) – 3 Layers	44
Figure 3-25: Thesis - Initial Water Saturation Map Files	45
Figure 3-26: Field Development.....	46
Figure 3-27: Completion Combinations	50
Figure 3-28: Reservoir Simulation Outputs.....	54
Figure 4-1: Top-Down Model Levels.....	58
Figure 4-2: Static Dataset Format	59

Figure 4-3: Dynamic Dataset Format	59
Figure 4-4: Formatted Static Data.....	60
Figure 4-5: Wellbore Diagram.....	61
Figure 4-6: Primary Data Exporting Formats	63
Figure 4-7: Simple Average Methods vs Weight Average Method Example	64
Figure 4-8: Spatio-temporal Database	66
Figure 4-9: Grid and Boundary	67
Figure 4-10: Static and Dynamic Spatial-Interpolation Using Inverse Distance Weighting Method	68
Figure 4-11: Reservoir Delineation using Voronoi Technique.....	69
Figure 4-12: Top-Down Modeling – History Match and Forecast	70
Figure 4-13: Scenario 1 - Development Dataset.....	72
Figure 4-14: Neural Network Data Preparation – Oil Model	73
Figure 4-15: Scenario 1 – TDM Input Attributes	75
Figure 4-16: Scenario 1 - Neural Network Data Partitioning	76
Figure 4-17: Scenario 1 – Partitioning Cross Plot Results	77
Figure 4-18: Scenario 2 - Development Dataset.....	78
Figure 4-19: Scenario 1 – TDM Input Attributes	80
Figure 4-20: Scenario 2 – Neural Network Data Partitioning	80
Figure 4-21: Scenario 2 – Partitioning Cross Plot Results	81
Figure 4-22: Scenario 3 – Development Dataset	82
Figure 4-23: Scenario 3 – TDM Input Attributes	84
Figure 4-24: Scenario 3 – Neural Network Data Partitioning	85
Figure 4-25: Scenario 3 – Partitioning Cross Plot Results	86

Figure 4-26: Scenario 4: Development and Deployment Datasets	87
Figure 4-27: Scenario 4 – TDM Input Attributes	90
Figure 4-28: Scenario 4 – Neural Network Data Partitioning	90
Figure 4-29: Scenario 4 – Partitioning Cross Plot Results	91
Figure 4-30: Scenario 5 – Development and Deployment Datasets	92
Figure 4-31: Scenario 5 – TDM Input Attributes	94
Figure 4-32: Scenario 5 – Neural Network Data Partitioning	95
Figure 4-33: Scenario 5 – Partitioning Cross Plot Results	96
Figure 5-1: Scenario 1 – Entire Field Production Profiles.....	102
Figure 5-2: Scenario 2 – Entire Field Production Profiles.....	103
Figure 5-3: Scenario 3 – Entire Field Production Profiles.....	104
Figure 5-4: Scenario 4 – Entire Field Production Profiles.....	105
Figure 5-5: Scenario 5 – Entire Field Production Profiles.....	106
Figure 5-6: Selected Dates for Distribution Maps During Validation and Forecast.....	107
Figure 5-7: Distribution Maps During Validation	111
Figure 5-8: Distribution Maps During Forecast.....	112
Figure 5-9: Good History Match of Individual Production Profiles.....	115
Figure 5-10: Average History Match of Individual Production Profiles	116
Figure 5-11: Poor History Match of Individual Production Profiles	117
Figure 5-12: Acceptable History Match of Production.....	122
Figure 5-13: Average History Match of Production	125
Figure 5-14: Poor Production History Match	127
Figure 5-15: Good Forecast Production.....	129
Figure 5-16: Average Forecast Production	131

Figure 5-17: Poor Production Forecast	133
Figure 7-1: Well-001 Biography.....	140
Figure 7-2: Well-002 Biography.....	141
Figure 7-3: Well-003 Biography.....	141
Figure 7-4: Well-004 Biography.....	142
Figure 7-5: Well-005 Biography	142
Figure 7-6: Well-006 Biography	143
Figure 7-7: Well-007 Biography	143
Figure 7-8: Well-008 Biography	144
Figure 7-9: Well-009 Biography	144
Figure 7-10: Well-010 Biography	145
Figure 7-11: Well-011 Biography	145
Figure 7-12: Well-012 Biography	146
Figure 7-13: Well-013 Biography	146
Figure 7-14: Well-014 Biography	147
Figure 7-15: Well-015 Biography	147
Figure 7-16: Well-016 Biography	148
Figure 7-17: Well-017 Biography	148
Figure 7-18: Well-018 Biography	149
Figure 7-19: Well-019 Biography	149
Figure 7-20: Well-020 Biography	150
Figure 7-21: Well-021 Biography	150
Figure 7-22: Well-022 Biography	151
Figure 7-23: Well-023 Biography	151

Figure 7-24: Well-024 Biography	152
Figure 7-25: Well-025 Biography	152
Figure 7-26: Well-026 Biography	153
Figure 7-27: Well-027 Biography	153
Figure 7-28: Well-028 Biography	154
Figure 7-29: Well-029 Biography	154
Figure 7-30: Well-030 Biography	155
Figure 7-31: Well-031 Biography	155
Figure 7-32: Well-032 Biography	156
Figure 7-33: Well-033 Biography	156
Figure 7-34: Well-034 Biography	157
Figure 7-35: Well-035 Biography	157
Figure 7-36: Well-036 Biography	158
Figure 7-37: Well-037 Biography	158
Figure 7-38: Well-038 Biography	159
Figure 7-39: Well-039 Biography	159
Figure 7-40: Well-040 Biography	160
Figure 7-41: Well-041 Biography	160
Figure 7-42: Well-042 Biography	161
Figure 7-43: Well-043 Biography	161
Figure 7-44: Well-044 Biography	162
Figure 7-45: Well-045 Biography	162
Figure 7-46: Well-046 Biography.....	163
Figure 7-47: Well-047 Biography.....	163

Figure 7-48: Well-048 Biography.....	164
Figure 7-49: Well-049 Biography.....	164
Figure 7-50: Well-050 Biography.....	165
Figure 7-51: Well-051 Biography.....	165
Figure 7-52: Well-052 Biography.....	166
Figure 7-53: Well-053 Biography.....	166
Figure 7-54: Well-054 Biography.....	167
Figure 7-55: Well-055 Biography.....	167
Figure 7-56: Well-056 Biography.....	168
Figure 7-57: Well-057 Biography.....	168
Figure 8-1: Oil Rate – Focal Static Attributes KPI.....	169
Figure 8-2: Oil Rate – Focal Dynamic Attributes KPI	170
Figure 8-3: Oil Rate – Offset Static Attributes KPI.....	170
Figure 8-4: Oil Rate – Offset Dynamic Attributes KPI	171
Figure 8-5: Gas Rate – Focal Static Attributes KPI.....	172
Figure 8-6: Gas Rate – Focal Dynamic Attributes KPI	172
Figure 8-7: Gas Rate – Offset Static Attributes KPI.....	173
Figure 8-8: Gas Rate – Offset Dynamic Attributes KPI	173
Figure 8-9: Water Rate – Focal Static Attributes KPI	174
Figure 8-10: Water Rate – Focal Dynamic Attributes KPI.....	174
Figure 8-11: Water Rate – Offset Static Attributes KPI	175
Figure 8-12: Water Rate – Offset Dynamic Attributes KPI	175
Figure 8-13: Reservoir Pressure – Focal Static Attributes KPI	176
Figure 8-14: Reservoir Pressure – Focal Dynamic Attributes KPI.....	176

Figure 8-15: Reservoir Pressure – Offset Static Attributes KPI	177
Figure 8-16: Reservoir Pressure – Offset Dynamic Attributes KPI	177
Figure 8-17: Water Saturation – Focal Static Attributes KPI	178
Figure 8-18: Water Saturation – Focal Dynamic Attributes KPI	178
Figure 8-19: Water Saturation – Offset Static Attributes KPI.....	179
Figure 8-20: Water Saturation – Focal Dynamic Attributes KPI	179
Figure 9-1: Scenario 1 - Oil Model Input Attributes	180
Figure 9-2: Scenario 1 - Gas Model Input Attributes	181
Figure 9-3: Scenario 1 - Water Model Input Attributes.....	182
Figure 9-4: Scenario 1 – Reservoir Pressure Model Input Attributes.....	183
Figure 9-5: Scenario 1 – Water Saturation Model Input Attributes.....	184
Figure 9-6: Scenario 1 – Entire Field Production	185
Figure 9-7: Scenario 1 – Well-003 Production History Match.....	186
Figure 9-8: Scenario 1 – Well-007 Production History Match.....	186
Figure 9-9: Scenario 1 – Well-009 Production History Match.....	187
Figure 9-10: Scenario 1 – Well-010 Production History Match.....	187
Figure 9-11: Scenario 1 – Well-015 Production History Match.....	188
Figure 9-12: Scenario 1 – Well-017 Production History Match.....	188
Figure 9-13: Scenario 1 – Well-018 Production History Match.....	189
Figure 9-14: Scenario 1 – Well-020 Production History Match.....	189
Figure 9-15: Scenario 1 – Well-021 Production History Match.....	190
Figure 9-16: Scenario 1 – Well-024 Production History Match.....	190
Figure 9-17: Scenario 1 – Well-025 Production History Match.....	191
Figure 9-18: Scenario 1 – Well-030 Production History Match.....	191

Figure 9-19: Scenario 1 – Well-031 Production History Match.....	192
Figure 9-20: Scenario 1 – Well-035 Production History Match.....	192
Figure 9-21: Scenario 1 – Well-036 Production History Match.....	193
Figure 9-22: Scenario 1 – Well-038 Production History Match.....	193
Figure 9-23: Scenario 1 – Well-040 Production History Match.....	194
Figure 9-24: Scenario 1 – Well-041 Production History Match.....	194
Figure 9-25: Scenario 1 – Well-045 Production History Match.....	195
Figure 9-26: Scenario 1 – Well-046 Production History Match.....	195
Figure 9-27: Scenario 1 – Well-047 Production History Match.....	196
Figure 9-28: Scenario 1 – Well-049 Production History Match.....	196
Figure 9-29: Scenario 1 – Well-050 Production History Match.....	197
Figure 9-30: Scenario 1 – Well-051 Production History Match.....	197
Figure 9-31: Scenario 1 – Well-052 Production History Match.....	198
Figure 9-32: Scenario 1 – Well-053 Production History Match.....	198
Figure 9-33: Scenario 1 – Well-056 Production History Match.....	199
Figure 9-34: Scenario 1 – Well-057 Production History Match.....	199
Figure 9-35: Scenario 1 – Well-001 Production History Match.....	200
Figure 9-36: Scenario 1 – Well-002 Production History Match.....	201
Figure 9-37: Scenario 1 – Well-004 Production History Match.....	201
Figure 9-38: Scenario 1 – Well-005 Production History Match.....	202
Figure 9-39: Scenario 1 – Well-006 Production History Match.....	202
Figure 9-40: Scenario 1 – Well-008 Production History Match.....	203
Figure 9-41: Scenario 1 – Well-011 Production History Match.....	203
Figure 9-42: Scenario 1 – Well-012 Production History Match.....	204

Figure 9-43: Scenario 1 – Well-013 Production History Match.....	204
Figure 9-44: Scenario 1 – Well-014 Production History Match.....	205
Figure 9-45: Scenario 1 – Well-016 Production History Match.....	205
Figure 9-46: Scenario 1 – Well-019 Production History Match.....	206
Figure 9-47: Scenario 1 – Well-022 Production History Match.....	206
Figure 9-48: Scenario 1 – Well-023 Production History Match.....	207
Figure 9-49: Scenario 1 – Well-026 Production History Match.....	207
Figure 9-50: Scenario 1 – Well-027 Production History Match.....	208
Figure 9-51: Scenario 1 – Well-028 Production History Match.....	208
Figure 9-52: Scenario 1 – Well-029 Production History Match.....	209
Figure 9-53: Scenario 1 – Well-032 Production History Match.....	209
Figure 9-54: Scenario 1 – Well-033 Production History Match.....	210
Figure 9-55: Scenario 1 – Well-034 Production History Match.....	210
Figure 9-56: Scenario 1 – Well-037 Production History Match.....	211
Figure 9-57: Scenario 1 – Well-039 Production History Match.....	211
Figure 9-58: Scenario 1 – Well-042 Production History Match.....	212
Figure 9-59: Scenario 1 – Well-043 Production History Match.....	212
Figure 9-60: Scenario 1 – Well-044 Production History Match.....	213
Figure 9-61: Scenario 1 – Well-054 Production History Match.....	213
Figure 9-62: Scenario 1 – Well-055 Production History Match.....	214
Figure 9-63: Scenario 1 – Well-048 Production History Match.....	215
Figure 9-64: Scenario 1 – Distribution Maps at Different Timesteps	219
Figure 10-1: Scenario 2 – Oil Model Input Attributes.....	220
Figure 10-2: Scenario 2 – Gas Model Input Attributes.....	221

Figure 10-3: Scenario 2 – Water Model Input Attributes	222
Figure 10-4: Scenario 2 – Reservoir Pressure Model Input Attributes.....	223
Figure 10-5: Scenario 2 – Water Saturation Model Input Attributes.....	224
Figure 10-6: Scenario 2 – Entire Field Production	225
Figure 10-7: Scenario 2 – Well-002 Production History Match.....	226
Figure 10-8: Scenario 2 – Well-004 Production History Match.....	227
Figure 10-9: Scenario 2 – Well-006 Production History Match.....	227
Figure 10-10: Scenario 2 – Well-007 Production History Match.....	228
Figure 10-11: Scenario 2 – Well-009 Production History Match.....	228
Figure 10-12: Scenario 2 – Well-010 Production History Match.....	229
Figure 10-13: Scenario 2 – Well-012 Production History Match.....	229
Figure 10-14: Scenario 2 – Well-013 Production History Match.....	230
Figure 10-15: Scenario 2 – Well-015 Production History Match.....	230
Figure 10-16: Scenario 2 – Well-017 Production History Match.....	231
Figure 10-17: Scenario 2 – Well-022 Production History Match.....	231
Figure 10-18: Scenario 2 – Well-024 Production History Match.....	232
Figure 10-19: Scenario 2 – Well-025 Production History Match.....	232
Figure 10-20: Scenario 2 – Well-027 Production History Match.....	233
Figure 10-21: Scenario 2 – Well-030 Production History Match.....	233
Figure 10-22: Scenario 2 – Well-031 Production History Match.....	234
Figure 10-23: Scenario 2 – Well-033 Production History Match.....	234
Figure 10-24: Scenario 2 – Well-035 Production History Match.....	235
Figure 10-25: Scenario 2 – Well-041 Production History Match.....	235
Figure 10-26: Scenario 2 – Well-045 Production History Match.....	236

Figure 10-27: Scenario 2 – Well-046 Production History Match.....	236
Figure 10-28: Scenario 2 – Well-047 Production History Match.....	237
Figure 10-29: Scenario 2 – Well-050 Production History Match.....	237
Figure 10-30: Scenario 2 – Well-051 Production History Match.....	238
Figure 10-31: Scenario 2 – Well-052 Production History Match.....	238
Figure 10-32: Scenario 2 – Well-053 Production History Match.....	239
Figure 10-33: Scenario 2 – Well-055 Production History Match.....	239
Figure 10-34: Scenario 2 – Well-057 Production History Match.....	240
Figure 10-35: Scenario 2 – Well-001 Production History Match.....	240
Figure 10-36: Scenario 2 – Well-003 Production History Match.....	241
Figure 10-37: Scenario 2 – Well-005 Production History Match.....	241
Figure 10-38: Scenario 2 – Well-008 Production History Match.....	242
Figure 10-39: Scenario 2 – Well-011 Production History Match.....	242
Figure 10-40: Scenario 2 – Well-014 Production History Match.....	243
Figure 10-41: Scenario 2 – Well-018 Production History Match.....	243
Figure 10-42: Scenario 2 – Well-019 Production History Match.....	244
Figure 10-43: Scenario 2 – Well-020 Production History Match.....	244
Figure 10-44: Scenario 2 – Well-021 Production History Match.....	245
Figure 10-45: Scenario 2 – Well-023 Production History Match.....	245
Figure 10-46: Scenario 2 – Well-026 Production History Match.....	246
Figure 10-47: Scenario 2 – Well-028 Production History Match.....	246
Figure 10-48: Scenario 2 – Well-029 Production History Match.....	247
Figure 10-49: Scenario 2 – Well-032 Production History Match.....	247
Figure 10-50: Scenario 2 – Well-034 Production History Match.....	248

Figure 10-51: Scenario 2 – Well-036 Production History Match.....	248
Figure 10-52: Scenario 2 – Well-037 Production History Match.....	249
Figure 10-53: Scenario 2 – Well-038 Production History Match.....	249
Figure 10-54: Scenario 2 – Well-039 Production History Match.....	250
Figure 10-55: Scenario 2 – Well-040 Production History Match.....	250
Figure 10-56: Scenario 2 – Well-042 Production History Match.....	251
Figure 10-57: Scenario 2 – Well-043 Production History Match.....	251
Figure 10-58: Scenario 2 – Well-044 Production History Match.....	252
Figure 10-59: Scenario 2 – Well-049 Production History Match.....	252
Figure 10-60: Scenario 2 – Well-054 Production History Match.....	253
Figure 10-61: Scenario 2 – Well-056 Production History Match.....	253
Figure 10-62: Scenario 2 – Well-016 Production History Match.....	254
Figure 10-63: Scenario 2 – Well-048 Production History Match.....	255
Figure 10-64: Scenario 2 – Distribution Maps at Different Timesteps	259
Figure 11-1: Scenario 3 – Oil Model Input Attributes.....	260
Figure 11-2: Scenario 3 – Gas Model Input Attributes.....	261
Figure 11-3: Scenario 3 – Water Model Input Attributes	262
Figure 11-4: Scenario 3 – Reservoir Pressure Model Input Attributes.....	263
Figure 11-5: Scenario 3 – Water Saturation Model Input Attributes.....	264
Figure 11-6: Scenario 3 – Entire Field Production	265
Figure 11-7: Scenario 3 – Well-002 Production History Match.....	266
Figure 11-8: Scenario 3 – Well-004 Production History Match.....	266
Figure 11-9: Scenario 3 – Well-006 Production History Match.....	267
Figure 11-10: Scenario 3 – Well-007 Production History Match.....	267

Figure 11-11: Scenario 3 – Well-009 Production History Match.....	268
Figure 11-12: Scenario 3 – Well-010 Production History Match.....	268
Figure 11-13: Scenario 3 – Well-015 Production History Match.....	269
Figure 11-14: Scenario 3 – Well-017 Production History Match.....	269
Figure 11-15: Scenario 3 – Well-019 Production History Match.....	270
Figure 11-16: Scenario 3 – Well-025 Production History Match.....	270
Figure 11-17: Scenario 3 – Well-030 Production History Match.....	271
Figure 11-18: Scenario 3 – Well-031 Production History Match.....	271
Figure 11-19: Scenario 3 – Well-035 Production History Match.....	272
Figure 11-20: Scenario 3 – Well-039 Production History Match.....	272
Figure 11-21: Scenario 3 – Well-041 Production History Match.....	273
Figure 11-22: Scenario 3 – Well-045 Production History Match.....	273
Figure 11-23: Scenario 3 – Well-046 Production History Match.....	274
Figure 11-24: Scenario 3 – Well-047 Production History Match.....	274
Figure 11-25: Scenario 3 – Well-050 Production History Match.....	275
Figure 11-26: Scenario 3 – Well-051 Production History Match.....	275
Figure 11-27: Scenario 3 – Well-055 Production History Match.....	276
Figure 11-28: Scenario 3 – Well-057 Production History Match.....	276
Figure 11-29: Scenario 3 – Well-001 Production History Match.....	277
Figure 11-30: Scenario 3 – Well-003 Production History Match.....	277
Figure 11-31: Scenario 3 – Well-005 Production History Match.....	278
Figure 11-32: Scenario 3 – Well-008 Production History Match.....	278
Figure 11-33: Scenario 3 – Well-011 Production History Match.....	279
Figure 11-34: Scenario 3 – Well-012 Production History Match.....	279

Figure 11-35: Scenario 3 – Well-013 Production History Match.....	280
Figure 11-36: Scenario 3 – Well-014 Production History Match.....	280
Figure 11-37: Scenario 3 – Well-016 Production History Match.....	281
Figure 11-38: Scenario 3 – Well-018 Production History Match.....	281
Figure 11-39: Scenario 3 – Well-020 Production History Match.....	282
Figure 11-40: Scenario 3 – Well-021 Production History Match.....	282
Figure 11-41: Scenario 3 – Well-022 Production History Match.....	283
Figure 11-42: Scenario 3 – Well-023 Production History Match.....	283
Figure 11-43: Scenario 3 – Well-024 Production History Match.....	284
Figure 11-44: Scenario 3 – Well-026 Production History Match.....	284
Figure 11-45: Scenario 3 – Well-027 Production History Match.....	285
Figure 11-46: Scenario 3 – Well-028 Production History Match.....	285
Figure 11-47: Scenario 3 – Well-029 Production History Match.....	286
Figure 11-48: Scenario 3 – Well-032 Production History Match.....	286
Figure 11-49: Scenario 3 – Well-033 Production History Match.....	287
Figure 11-50: Scenario 3 – Well-034 Production History Match.....	287
Figure 11-51: Scenario 3 – Well-037 Production History Match.....	288
Figure 11-52: Scenario 3 – Well-038 Production History Match.....	288
Figure 11-53: Scenario 3 – Well-040 Production History Match.....	289
Figure 11-54: Scenario 3 – Well-042 Production History Match.....	289
Figure 11-55: Scenario 3 – Well-043 Production History Match.....	290
Figure 11-56: Scenario 3 – Well-044 Production History Match.....	290
Figure 11-57: Scenario 3 – Well-049 Production History Match.....	291
Figure 11-58: Scenario 3 – Well-052 Production History Match.....	291

Figure 11-59: Scenario 3 – Well-053 Production History Match.....	292
Figure 11-60: Scenario 3 – Well-056 Production History Match.....	292
Figure 11-61: Scenario 3 – Well-036 Production History Match.....	293
Figure 11-62: Scenario 3 – Well-048 Production History Match.....	293
Figure 11-63: Scenario 3 – Well-054 Production History Match.....	294
Figure 11-64: Scenario 3 – Distribution Maps at Different Timesteps	298
Figure 12-1: Scenario 4 – Oil Model Input Attributes.....	299
Figure 12-2: Scenario 4 – Gas Model Input Attributes.....	300
Figure 12-3: Scenario 4 – Water Model Input Attributes	301
Figure 12-4: Scenario 4 – Reservoir Pressure Model Input Attributes.....	302
Figure 12-5: Scenario 4 – Water Saturation Model Input Attributes.....	303
Figure 12-6: Scenario 4 – Entire Field Production	304
Figure 12-7: Scenario 4 – Well-001 Production History Match.....	305
Figure 12-8: Scenario 4 – Well-003 Production History Match.....	305
Figure 12-9: Scenario 4 – Well-006 Production History Match.....	306
Figure 12-10: Scenario 4 – Well-009 Production History Match.....	306
Figure 12-11: Scenario 4 – Well-010 Production History Match.....	307
Figure 12-12: Scenario 4 – Well-013 Production History Match.....	307
Figure 12-13: Scenario 4 – Well-014 Production History Match.....	308
Figure 12-14: Scenario 4 – Well-015 Production History Match.....	308
Figure 12-15: Scenario 4 – Well-018 Production History Match.....	309
Figure 12-16: Scenario 4 – Well-019 Production History Match.....	309
Figure 12-17: Scenario 4 – Well-020 Production History Match.....	310
Figure 12-18: Scenario 4 – Well-022 Production History Match.....	310

Figure 12-19: Scenario 4 – Well-023 Production History Match.....	311
Figure 12-20: Scenario 4 – Well-024 Production History Match.....	311
Figure 12-21: Scenario 4 – Well-025 Production History Match.....	312
Figure 12-22: Scenario 4 – Well-027 Production History Match.....	312
Figure 12-23: Scenario 4 – Well-029 Production History Match.....	313
Figure 12-24: Scenario 4 – Well-030 Production History Match.....	313
Figure 12-25: Scenario 4 – Well-031 Production History Match.....	314
Figure 12-26: Scenario 4 – Well-033 Production History Match.....	314
Figure 12-27: Scenario 4 – Well-034 Production History Match.....	315
Figure 12-28: Scenario 4 – Well-035 Production History Match.....	315
Figure 12-29: Scenario 4 – Well-036 Production History Match.....	316
Figure 12-30: Scenario 4 – Well-038 Production History Match.....	316
Figure 12-31: Scenario 4 – Well-040 Production History Match.....	317
Figure 12-32: Scenario 4 – Well-041 Production History Match.....	317
Figure 12-33: Scenario 4 – Well-042 Production History Match.....	318
Figure 12-34: Scenario 4 – Well-043 Production History Match.....	318
Figure 12-35: Scenario 4 – Well-045 Production History Match.....	319
Figure 12-36: Scenario 4 – Well-047 Production History Match.....	319
Figure 12-37: Scenario 4 – Well-048 Production History Match.....	320
Figure 12-38: Scenario 4 – Well-049 Production History Match.....	320
Figure 12-39: Scenario 4 – Well-050 Production History Match.....	321
Figure 12-40: Scenario 4 – Well-051 Production History Match.....	321
Figure 12-41: Scenario 4 – Well-052 Production History Match.....	322
Figure 12-42: Scenario 4 – Well-053 Production History Match.....	322

Figure 12-43: Scenario 4 – Well-054 Production History Match.....	323
Figure 12-44: Scenario 4 – Well-055 Production History Match.....	323
Figure 12-45: Scenario 4 – Well-056 Production History Match.....	324
Figure 12-46: Scenario 4 – Well-057 Production History Match.....	324
Figure 12-47: Scenario 4 – Well-002 Production History Match.....	325
Figure 12-48: Scenario 4 – Well-004 Production History Match.....	325
Figure 12-49: Scenario 4 – Well-005 Production History Match.....	326
Figure 12-50: Scenario 4 – Well-007 Production History Match.....	326
Figure 12-51: Scenario 4 – Well-008 Production History Match.....	327
Figure 12-52: Scenario 4 – Well-012 Production History Match.....	327
Figure 12-53: Scenario 4 – Well-016 Production History Match.....	328
Figure 12-54: Scenario 4 – Well-017 Production History Match.....	328
Figure 12-55: Scenario 4 – Well-021 Production History Match.....	329
Figure 12-56: Scenario 4 – Well-026 Production History Match.....	329
Figure 12-57: Scenario 4 – Well-028 Production History Match.....	330
Figure 12-58: Scenario 4 – Well-032 Production History Match.....	330
Figure 12-59: Scenario 4 – Well-037 Production History Match.....	331
Figure 12-60: Scenario 4 – Well-039 Production History Match.....	331
Figure 12-61: Scenario 4 – Well-044 Production History Match.....	332
Figure 12-62: Scenario 4 – Well-046 Production History Match.....	332
Figure 12-63: Scenario 4 – Well-002 Forecast Production	335
Figure 12-64: Scenario 4 – Well-010 Forecast Production	335
Figure 12-65: Scenario 4 – Well-013 Forecast Production	336
Figure 12-66: Scenario 4 – Well-019 Forecast Production	336

Figure 12-67: Scenario 4 – Well-022 Forecast Production	337
Figure 12-68: Scenario 4 – Well-023 Forecast Production	337
Figure 12-69: Scenario 4 – Well-024 Forecast Production	338
Figure 12-70: Scenario 4 – Well-048 Forecast Production	338
Figure 12-71: Scenario 4 – Well-053 Forecast Production	339
Figure 12-72: Scenario 4 – Well-057 Forecast Production	339
Figure 12-73: Scenario 4 – Well-017 Forecast Production	340
Figure 12-74: Scenario 4 – Well-025 Forecast Production	340
Figure 12-75: Scenario 4 – Well-027 Forecast Production	341
Figure 12-76: Scenario 4 – Well-031 Forecast Production	341
Figure 12-77: Scenario 4 – Well-034 Forecast Production	342
Figure 12-78: Scenario 4 – Well-041 Forecast Production	342
Figure 12-79: Scenario 4 – Well-042 Forecast Production	343
Figure 12-80: Scenario 4 – Well-043 Forecast Production	343
Figure 12-81: Scenario 4 – Well-047 Forecast Production	344
Figure 12-82: Scenario 4 – Well-049 Forecast Production	344
Figure 12-83: Scenario 4 – Well-051 Forecast Production	345
Figure 12-84: Scenario 4 – Well-003 Forecast Production	346
Figure 12-85: Scenario 4 – Well-015 Forecast Production	346
Figure 12-86: Scenario 4 – Well-032 Forecast Production	347
Figure 12-87: Scenario 4 – Well-036 Forecast Production	347
Figure 12-88: Scenario 4 – Well-038 Forecast Production	348
Figure 12-89: Scenario 4 – Well-039 Forecast Production	348
Figure 12-90: Scenario 4 – Well-040 Forecast Production	349

Figure 12-91: Scenario 4 – Well-044 Forecast Production	349
Figure 12-92: Scenario 4 – Well-050 Forecast Production	350
Figure 12-93: Scenario 4 – Well-052 Forecast Production	350
Figure 12-94: Scenario 4 – Well-054 Forecast Production	351
Figure 12-95: Scenario 4 – Well-055 Forecast Production	351
Figure 12-96: Scenario 4 – Well-056 Forecast Production	352
Figure 12-97: Scenario 4 – Distribution Maps at Different Timesteps	356
Figure 13-1: Scenario 5 – Oil Model Input Attributes.....	357
Figure 13-2: Scenario 5 – Gas Model Input Attributes.....	358
Figure 13-3: Scenario 5 – Water Model Input Attributes	359
Figure 13-4: Scenario 5 – Reservoir Pressure Model Input Attributes.....	360
Figure 13-5: Scenario 5 – Water Saturation Model Input Attributes.....	361
Figure 13-6: Scenario 5 – Entire Field Production	362
Figure 13-7: Scenario 5 – Well-002 Production History Match.....	363
Figure 13-8: Scenario 5 – Well-007 Production History Match.....	363
Figure 13-9: Scenario 5 – Well-009 Production History Match.....	364
Figure 13-10: Scenario 5 – Well-010 Production History Match.....	364
Figure 13-11: Scenario 5 – Well-013 Production History Match.....	365
Figure 13-12: Scenario 5 – Well-015 Production History Match.....	365
Figure 13-13: Scenario 5 – Well-018 Production History Match.....	366
Figure 13-14: Scenario 5 – Well-019 Production History Match.....	366
Figure 13-15: Scenario 5 – Well-020 Production History Match.....	367
Figure 13-16: Scenario 5 – Well-021 Production History Match.....	367
Figure 13-17: Scenario 5 – Well-022 Production History Match.....	368

Figure 13-18: Scenario 5 – Well-023 Production History Match.....	368
Figure 13-19: Scenario 5 – Well-024 Production History Match.....	369
Figure 13-20: Scenario 5 – Well-025 Production History Match.....	369
Figure 13-21: Scenario 5 – Well-027 Production History Match.....	370
Figure 13-22: Scenario 5 – Well-030 Production History Match.....	370
Figure 13-23: Scenario 5 – Well-031 Production History Match.....	371
Figure 13-24: Scenario 5 – Well-035 Production History Match.....	371
Figure 13-25: Scenario 5 – Well-038 Production History Match.....	372
Figure 13-26: Scenario 5 – Well-040 Production History Match.....	372
Figure 13-27: Scenario 5 – Well-041 Production History Match.....	373
Figure 13-28: Scenario 5 – Well-042 Production History Match.....	373
Figure 13-29: Scenario 5 – Well-043 Production History Match.....	374
Figure 13-30: Scenario 5 – Well-047 Production History Match.....	374
Figure 13-31: Scenario 5 – Well-049 Production History Match.....	375
Figure 13-32: Scenario 5 – Well-051 Production History Match.....	375
Figure 13-33: Scenario 5 – Well-053 Production History Match.....	376
Figure 13-34: Scenario 5 – Well-055 Production History Match.....	376
Figure 13-35: Scenario 5 – Well-057 Production History Match.....	377
Figure 13-36: Scenario 5 – Well-001 Production History Match.....	378
Figure 13-37: Scenario 5 – Well-003 Production History Match.....	378
Figure 13-38: Scenario 5 – Well-004 Production History Match.....	379
Figure 13-39: Scenario 5 – Well-005 Production History Match.....	379
Figure 13-40: Scenario 5 – Well-006 Production History Match.....	380
Figure 13-41: Scenario 5 – Well-008 Production History Match.....	380

Figure 13-42: Scenario 5 – Well-011 Production History Match.....	381
Figure 13-43: Scenario 5 – Well-012 Production History Match.....	381
Figure 13-44: Scenario 5 – Well-014 Production History Match.....	382
Figure 13-45: Scenario 5 – Well-017 Production History Match.....	382
Figure 13-46: Scenario 5 – Well-026 Production History Match.....	383
Figure 13-47: Scenario 5 – Well-028 Production History Match.....	383
Figure 13-48: Scenario 5 – Well-029 Production History Match.....	384
Figure 13-49: Scenario 5 – Well-032 Production History Match.....	384
Figure 13-50: Scenario 5 – Well-033 Production History Match.....	385
Figure 13-51: Scenario 5 – Well-034 Production History Match.....	385
Figure 13-52: Scenario 5 – Well-036 Production History Match.....	386
Figure 13-53: Scenario 5 – Well-037 Production History Match.....	386
Figure 13-54: Scenario 5 – Well-039 Production History Match.....	387
Figure 13-55: Scenario 5 – Well-044 Production History Match.....	387
Figure 13-56: Scenario 5 – Well-045 Production History Match.....	388
Figure 13-57: Scenario 5 – Well-048 Production History Match.....	388
Figure 13-58: Scenario 5 – Well-050 Production History Match.....	389
Figure 13-59: Scenario 5 – Well-052 Production History Match.....	389
Figure 13-60: Scenario 5 – Well-054 Production History Match.....	390
Figure 13-61: Scenario 5 – Well-056 Production History Match.....	390
Figure 13-62: Scenario 5 – Well-016 Production History Match.....	391
Figure 13-63: Scenario 5 – Well-002 Forecast Production	392
Figure 13-64: Scenario 5 – Well-010 Forecast Production	392
Figure 13-65: Scenario 5 – Well-015 Forecast Production	393

Figure 13-66: Scenario 5 – Well-029 Forecast Production	393
Figure 13-67: Scenario 5 – Well-031 Forecast Production	394
Figure 13-68: Scenario 5 – Well-035 Forecast Production	394
Figure 13-69: Scenario 5 – Well-042 Forecast Production	395
Figure 13-70: Scenario 5 – Well-044 Forecast Production	395
Figure 13-71: Scenario 5 – Well-047 Forecast Production	396
Figure 13-72: Scenario 5 – Well-049 Forecast Production	396
Figure 13-73: Scenario 5 – Well-051 Forecast Production	397
Figure 13-74: Scenario 5 – Well-013 Forecast Production	398
Figure 13-75: Scenario 5 – Well-017 Forecast Production	398
Figure 13-76: Scenario 5 – Well-019 Forecast Production	399
Figure 13-77: Scenario 5 – Well-022 Forecast Production	399
Figure 13-78: Scenario 5 – Well-023 Forecast Production	400
Figure 13-79: Scenario 5 – Well-024 Forecast Production	400
Figure 13-80: Scenario 5 – Well-027 Forecast Production	401
Figure 13-81: Scenario 5 – Well-032 Forecast Production	401
Figure 13-82: Scenario 5 – Well-034 Forecast Production	402
Figure 13-83: Scenario 5 – Well-036 Forecast Production	402
Figure 13-84: Scenario 5 – Well-038 Forecast Production	403
Figure 13-85: Scenario 5 – Well-039 Forecast Production	403
Figure 13-86: Scenario 5 – Well-040 Forecast Production	404
Figure 13-87: Scenario 5 – Well-041 Forecast Production	404
Figure 13-88: Scenario 5 – Well-043 Forecast Production	405
Figure 13-89: Scenario 5 – Well-045 Forecast Production	405

Figure 13-90: Scenario 5 – Well-050 Forecast Production	406
Figure 13-91: Scenario 5 – Well-052 Forecast Production	406
Figure 13-92: Scenario 5 – Well-055 Forecast Production	407
Figure 13-93: Scenario 5 – Well-003 Forecast Production	408
Figure 13-94: Scenario 5 – Well-025 Forecast Production	408
Figure 13-95: Scenario 5 – Well-048 Forecast Production	409
Figure 13-96: Scenario 5 – Well-053 Forecast Production	409
Figure 13-97: Scenario 5 – Well-054 Forecast Production	410
Figure 13-98: Scenario 5 – Well-056 Forecast Production	410
Figure 13-99: Scenario 5 – Well-057 Production History Match.....	411
Figure 13-100: Scenario 5 – Distribution Maps at Different Timesteps	415

List of Tables

Table 3-1: Original Model – Properties Overview	22
Table 3-2: Fluid Component Characteristics	30
Table 3-3: Combining Layers Into Single Layer	34
Table 3-4: Grid Modification Process.....	38
Table 3-5: Field Characteristics	45
Table 3-6: Field Development Phases	46
Table 3-7: Well Events	49
Table 3-8: Field Completion Plan.....	51
Table 3-9: Field Production	53
Table 3-10: Cumulative Production Statistics on a Well Basis	53
Table 3-11: Well Based Reported Data	54
Table 3-12: Layer Based Reported Data.....	55
Table 3-13: Special History Reported Data	55
Table 3-14: Block Properties Reported Data	55
Table 4-1: History Match and Forecast Scenarios – Description	71
Table 4-2: Partitioning No. of Records	97
Table 4-3: Predictive Model Input Attributes and No. of Epochs Summary.....	97
Table 4-4: TDM Model R.Squared Results	98
Table 4-5: TDM Model MAE Results	98
Table 5-1: History Match – Cumulative Field Production Comparison.....	100
Table 5-2: History Match and Forecast – Cumulative Field Production	101
Table 5-3: History Match Accuracy of Individual Production Rates	118

Table 5-4: Forecast of Individual Production Rates	119
Table 5-5: History Match Production Accuracy	133
Table 5-6: Production Forecast.....	133

List of Equations

Eq. 2-1	8
Eq. 2-2	8
Eq. 2-3	9
Eq. 4-1	64
Eq. 4-2	65
Eq. 4-3	65

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Symbols and Abbreviations

Term	Description
AI	Artificial Intelligence
ANN	Artificial Neural Networks
DDM	Data-Driven Modeling
KPI	Key Performance Indicators
MAE	Mean Absolute Error
ML	Machine Learning
TDM	Top-Down Modeling

CHAPTER 1

1 INTRODUCTION

The oil and natural gas industry provide a reliable source of energy to the world that is sufficient to power industries, heat homes, allow efficient transportation and more. Extracting oil and natural gas from thousands of feet below the Earth's surface encompasses a series of steps; from the exploration stage to the production stage, petroleum engineers continue to innovate and enhance technologies to produce in a safe and profitable manner as expenditures, time, and operational risks are associated in the process [1].

Reservoir modeling allows experts to model the behavior of fluid flow in porous media when access to these reservoirs is not physically possible. Additionally, reservoir modeling allows experts to analyze and interpret data that enables improvements in the production planning, which is a crucial step in the decision-making process of drilling successful new wells.

Some of the traditional approaches used in modeling complex data structures, analyzing and optimizing field production require sophisticated equipment that can be often computationally expensive and time consuming. RTA (Rate Transient Analysis) and DCA (Decline Curve Analysis) have been reliable tools for reservoir modeling. Nevertheless, these are old fashioned approaches that have been around for decades and that add little insight to operations [2].

Currently, the amount of available data, measured or generated, can be used by Artificial Intelligence and Machine Learning algorithms that are capable of learning from past behaviors to provide accurate predictions – history matching and forecasting in the context of oil and gas [2].

1.1 Problem statement

This thesis focuses on the applications of reservoir modeling through two different approaches:

1. Traditional Numerical Reservoir Simulation and Modeling
2. Data-Driven Reservoir Simulation and Modeling

The first is a conventional approach that uses numerical simulations to solve an engineering problem. The second acknowledges the capabilities of artificial intelligence and machine learning to look at reservoir modeling through a different point of view; more specifically through the applications of artificial neural networks [3].

The objective of this thesis is to test and validate the capabilities of Artificial Intelligence (AI) and Machine Learning (ML) by using synthetic data generated from a numerical reservoir model with efforts to create a data-driven reservoir model. The success of the application of these technologies will be determined by the proximity of the data-driven model's predicted data against the numerical simulation actual data.

1.2 Thesis Outline

This thesis is divided into the following chapters:

Chapter 1: discusses two current approaches to reservoir modeling and states the objective of the thesis.

Chapter 2: provides a background on numerical simulation, artificial intelligence and machine learning, and the application of artificial neural networks and literature review of previous studies performed on data-driven modeling.

Chapter 3: describes the details of a numerical reservoir model, the modifications performed on the original model and the data exported from the finalized working model (thesis model).

Chapter 4: elaborates on the development of 5 different top-down models using data generated from a numerical reservoir model.

Chapter 5: discusses the results (history match and forecast) obtained from the data-driven reservoir model and compares it to the actual data (numerical reservoir model).

Chapter 6: concludes the thesis and potential future work.

CHAPTER 2

2 LITERATURE REVIEW

The following chapter provides some background information on (1) numerical simulation, a conventional reservoir modeling approach, (2) the theory and application of machine learning through algorithmic methods such as artificial neural networks and (3) previous work performed on the application of machine learning in the oil and gas industry.

2.1 Numerical Simulation

Numerical simulation is a mathematical representation of a physical behavior based on relevant hypothesis and simplified assumptions [4]. Darcy's law is one of the most commonly used models in the oil industry that describes how fluids flow in porous media. The equations associated with solving Darcy flow problems are fairly complex and difficult to solve analytically. As a result, oversimplified linear systems of equations are solved by utilizing memory efficient and parallelizable algorithms [5].

A few steps must be taken in preparation to build a numerical reservoir model. First, the representation of the physical domain is defined by a grid system. A set of pre-defined specifications must be provided; otherwise, default values are used in place. Once the model is physically established, a numerous set of calculations are computed at each grid block with efforts to find a numerical solution that provides some insight about the model's behavior. For example, pressures, saturations, and production rates are obtained after several hours of running a single simulation. The time and computational work from the numerical simulation process often depend on the quality and size of the grids as well as the complexity level of the reservoir model. Mesh refinement is a very important factor for determining an accurate solution. [6].

The second step is to validate the numerical reservoir model by comparing its results against actual measured data. This process is known as history matching. As the name implies, multiple attempts are made to match real measurements (often oil rate history) by modifying the reservoir properties

of the numerical model. This process may take weeks, months, or years until the model successfully matches history. Once a reservoir model is finalized, calibrated and history matched, it will be used for reservoir planning, forecasting, and investment decisions [7].

Besides numeric modeling possibly taking a significant length of time to generate an accurate reservoir model, it can be incredibly costly. As a result, engineers have long searched for a more efficient and effective method of creating a reservoir model.

2.2 Machine Learning

Artificial intelligence is a term that dates back to the 1950's when mathematicians were interested in making intelligent machines capable of learning and problem solving [8].

Machine Learning is a subset of AI and was first defined by Arthur Samuel as “the field of study that gives computers the ability to learn without being explicitly programmed.” This definition was reiterated by Tom Mitchell when he proposed that computer programs are said to learn from experience and these improve their performance with respect to some class of tasks [9].

One of the common techniques in machine learning is the application of Artificial Neural Networks (ANN). Artificial Neural Networks are simple mathematical computational algorithms capable of learning from input data and discovering patterns in data (pattern recognition). In the context of reservoir modeling, “machine learning algorithms are trained to model the physics of the phenomena that are of interest”. [10]. The application of these technologies does not rely on complex systems of equations or assumptions that are often made in numerical reservoir simulations. Instead, it relies on the quantity and quality of data that the system can learn from to achieve specific goals through flexible adaptation [8].

2.2.1 The Neuron

Artificial Neural Networks (ANN) are inspired by the physical, biological, and chemical processes that take place in the human brain and have been developed in efforts to understand and replicated how humans learn.

Figure 2-1: Biological Neuron's Structure

In a human brain, millions of neurons exist to receive and carry information. This information is also known as nerve impulses. The main parts of a neuron are the cell body that contains the nucleus and other organelles, dendrites that receive the electrical signal from other neurons, and the axon that passes the information to other neurons. Notice that the cell body is in between the two extremes of the neuron (dendrites and axon). The electrical impulses travel from one neuron to another via synapse, where thousands of dendrites from a neuron meet the axon of another neuron [11].

2.2.2 Artificial Neuron – Structure Replication

In a similar fashion, artificial neural networks mainly consist of an input layer, an output layer, and hidden layers. The input layers are similar to a neuron's dendrites, which are made of a set of artificial neurons that receive information from a dataset. As a matter of fact, this information helps the neural network learn.

The output layer is similar to the neuron's axon; it responds to the information passed

to the neural network and determines whether the system has learned the information. Finally, the hidden layers exist to communicate the information between the input and output layers [12].

Figure 2-2 illustrates a neuron's structure replication from a biological neuron's structure that receives, carries, and processes information.

Figure 2-2: Artificial Neural Network Structure

2.2.3 Artificial Neural Networks

As mentioned previously, the architecture of an artificial neural network is often composed of an input layer, a hidden layer, and an output layer. Biologically, the information carried from one neuron to another travels via synapse. Similarly, the strength of the connection between two artificial neurons is represented by weights. The value of each weight determines the strength of the information being fed forward through the neural network. In the context of reservoir modeling, permeability, flowing bottom-hole pressure, and well location have unique contributions to the reservoir's oil production. Therefore, the strength of weight values assigned to each attribute varies, depending on the relationship an attribute has with respect to the output value.

Artificial neural networks seek to strengthen their connections by a process called backpropagation. This process aims to optimize the set of weights assigned to the input neurons with efforts to develop a well-trained predictive model and minimize the total error between the actual output value and the predicted output value.

Behavior replication

The mathematical representation of an artificial neural network is depicted in Figure 2-3.

Figure 2-3: Mathematical Representation of a Neural Network

The flow of information starts at the input layers, where a pre-processed target dataset, referred to as the spatio-temporal database in the context of data-driven reservoir modeling, is fed to the system. A transfer function (or transfer potential) is performed on the inputs and their respective weights. The result from the transfer function is passed into a non-linear activation function, $f(x)$, that determines an output value within a determined range. The output value is then passed to the next neuron layer where the same procedure is repeated [13].

The mathematical procedure is summarized into the following steps:

1. Transfer function
2. Activation function
3. Error function
4. Backpropagation
5. Weight optimization

The **transfer function** is the dot product, or the sum of products of the inputs and the weights. It is important to note that even if the value used from the input neurons is the same, the output values will change based on the weight values assigned. The values of these weights determine the strength of the pathways between neuron layers [14].

$$\theta = \sum x_1 w_{1j} + x_2 w_{2j} + x_3 w_{3j} + \cdots + x_n w_{nj} \quad \text{Eq. 2-1}$$

A non-linear and differentiable **activation function** is applied to the result of the transfer function or the sum of the products. The activation function yields an output that is then passed on to the next layer.

Activation functions bring non-linearity to the system which translates to the neural network being able to learn complex systems. Based on the type of data used in training, negative values in the dataset can be handled with proper implementation of activation functions. Tanh outputs values between -1 and 1. Leaky relu keeps some of the negative values in a dataset. Logistic sigmoid displays values from 0 to 1 based on the value obtained from the transfer function [14]. Notice the non-linearity of the activation function in Figure 2-4.

$$f(\theta) = \frac{1}{1 + e^{-\theta}} \quad \text{Eq. 2-2}$$

Figure 2-4: Logistic Sigmoid Activation Function

Figure 2-5: Tanh Activation Function

Figure 2-6: Leaky Relu Activation Function

Figure 2-7: MISH Activation Function

The output value calculated at the last hidden layer is compared to the actual output value from the target dataset. The total error is calculated using an **error function** such as Error Sum of Squared (ESS) shown in Eq. 2-3 [14].

$$ESS = \sum_{i=1}^n \frac{1}{2} (Y_{Target} - Y_{output})^2 \quad \text{Eq. 2-3}$$

The final goal is to minimize the error by updating and correcting all of the weights in the neural network. This process is known as backpropagation. **Backpropagation** is a training algorithm used in supervised learning using the gradient descent method that modifies the weights of a neural network with efforts to reduce the total error between the calculated output of the neural network and the actual output from the target dataset [15].

2.2.4 Datasets

The data used in machine learning and the development of predictive models is often separated into different datasets:

- Training dataset
- Calibration dataset
- Verification or validation dataset

The input layer represents the values of attributes that come from external data. For example, reservoir characteristics, operational constraints, and production measurements can be used as input attributes for a neural network to learn from. If the neural network sees and learns from the data, it means that the data is part of the training dataset.

During training, the neural network continues to learn from the same data as the weights continue to be optimized in efforts minimize the loss function (total error). The calibration dataset is separate from the training dataset and ensures that the model is not overfitting (memorizing the training dataset) or under fitting (not learning).

Lastly, the verification or validation dataset is completely separate from both the training and calibration datasets and it is used to evaluate the performance of the trained and calibrated model [16].

2.2.5 Data Partitioning

In the context of reservoir modeling, the sequential structure in which each dataset is presented to the neural network impacts the quality of the results and the degree of confidence on the final predictive model. Three types of partitioning (history matching techniques) are discussed:

1. Sequential partitioning
2. Random partitioning
3. Mixed partitioning

The sequential partitioning presents records in the exact order in which these have been arranged in the target dataset. If the data has been arranged based on a timeline, the training, calibration and verification datasets are arranged in the same manner, honoring the sequence of the data. This is the most robust technique used in the development of a data-driven reservoir model [17].

The random partitioning assigns data to the training, calibration and verification datasets in a completely random manner. Due to the nature of this data partitioning type, the sequence of a timeline is not honored and therefore it is not treated as a blind history match. Note that reservoir engineers attempt to history match and forecast a sequential period of time. Therefore, random partitioning is the least robust technique [17].

Lastly, the mixed partitioning, also referred to as multi-random partitioning, is a combination between the sequential and the random partitioning types. While the training and calibration datasets contain randomized data, the verification dataset contains data located at the end of the target dataset [17].

Figure 2-8 depicts the three types of partitioning techniques previously discussed.

Figure 2-8: Data Partitioning Techniques

2.3 Data Mining

Data mining is focused on the process of discovering patterns in large sets of data. However, in order for machine learning algorithms to properly discover such patterns, data pre-processing, a data mining technique, is used to cleanse and prepare the collected data into a useful and standardized format. A brief schematic of important data mining steps is depicted in Figure 2-9 [18].

Figure 2-9: Data Mining Steps

2.4 Previous Work

Previous studies acknowledge the capabilities of AI and ML techniques as these continue to demonstrate that machines have the ability to interpret and learn from external data with efforts to accurately history match and project future possibilities (forecasting) [19].

Yara Alatrach conducted a study on a low permeability carbonate reservoir located in Abu Dhabi. His study implemented Artificial Neural Networks in the development of a data-driven reservoir model that could learn from past historical data to optimize production and injection to maximize production of the entire field. The main objective of this study was to compare traditional numerical modeling approaches against alternative methods and techniques that honor the physics of a reservoir by using actual field measurements such as seismic surveys, well logs, core analysis, well tests, well production and injection behavior among others. Oil, gas, and water productions, reservoir pressure and water saturation results from the predictive model are compared against the actual data collected from the field are shown in Figure 2-10 [20].

Figure 2-10: TDM prediction against historical Production of Well A [20]

In the same context of reservoir modeling, Hassan Al Haifi demonstrated that data-driven reservoir modeling is a complete alternative to numerical reservoir modeling and that can serve as an appropriate tool for reservoir management. He also emphasized some of the challenges using artificial intelligence and machine learning as these technologies require large amount of quality data to be able to obtaine an accurate predictive model. The history match and forecasting results from the predictive model are compared to the original data generated from a numerical simulation in Figure 2-11.

Figure 2-11: History Match and Forecasting Results for Oil (A), Gas (B) and Water (C) the Entire Reservoir

Determining well productivity influences the design and completion of a well. Significant estimations of well productivity have been conducted through the implementation of equations

and correlations in numerical simulations. Amjed Hassan et al. presented a study to determine well productivity of fishbone wells by implementing 3 different artificial intelligence techniques that aim to reduce the uncertainty associated with numerical simulations. The implementation of Artificial Neural Networks in his study resulted in acceptable matches between the predicted and actual flowrates for fishbone wells. After investigating different case scenarios, a 7.23% average absolute error and a correlation coefficient of 0.979 was obtained. The training and testing results using Artificial Neural Networks is shown in Figure 2-12 [21].

Figure 2-12: Comparison between the predicted and the target flow rate ratio (Q/Q_{max}) using the ANN model for the (A) training and (B) testing datasets [21]

Well logs are used in the industry to assist petroleum engineers evaluate and allocate the presence of hydrocarbons in a potential reservoir (formation evaluation). It is often the case that well log data is may not be available or it is incomplete. Marwan Alnuaimi successfully used RNN (Regression Neural Networks) to generate synthetic well logs when the information was missing from a particular well log. The application of RNN assisted enhanced the learning process from a variety of well logs representing the physics of the reservoir. Figure 2-13 illustrates the neural network development results.

(A)

(B)

(C)

(D)

Figure 2-13: Neural Network Development Results for Training (A), Calibration (B), Verification (C) and Blind (D) datasets

The generated synthetic well logs for effective porosity are illustrated below and compared to the actual effective porosity values in Figure 2-14.

Figure 2-14: Generated output “NN-PHIE” and actual value “PHIE”

Other applications to study fluid behavior in oil and gas reservoirs is the development of smart proxy models. Due to the complexity of the reservoirs, expensive and sophisticated equipment is required to run these types of simulations and therefore, become time-consuming. Smart proxy models are an alternative to numerical simulations that assists reservoir engineers in reservoir development and production management [22].

CHAPTER 3

3 NUMERICAL RESERVOIR MODELING

This chapter is divided into three sections. The first section elaborates on the specifications of a numerical reservoir model created by a group of students at West Virginia University using CMG, a commercial numerical simulator. The model was further modified and provided by Joshua Dietz in order to accomplish the objectives of thesis. The second section describes the modifications performed on the original model with efforts to approach real-field events. The last section provides information of the data exported from the conducted numerical simulation of the finalized numerical reservoir model version.

Figure 3-1 provides a visual workflow for the development of the thesis, where an original numerical reservoir model, “Model A” in Figure 3-1, was provided as the foundation of a further developed and far more complex reservoir model, “Model B” in Figure 3-1. The data obtained from the more complex reservoir model was used for the development of a data-driven reservoir model.

The numerical reservoir simulation results are to be compared to the results obtained from the data-driven reservoir model.

Figure 3-1: Thesis Workflow

3.1 Original Numerical Reservoir Model

A 6 layered under saturated reservoir was originally created using Builder (a module supported by CMG simulators) by a group of students at West Virginia University. The general properties of the field are listed below and discussed into more detail in the following sections:

- a. Reservoir Model Overview
- b. Grid construction and structure
- c. Reservoir characteristics
- d. Description of flowing components
- e. Rock fluid properties
- f. Initial conditions
- g. Numerical controls
- h. Allocation of wells with their respective production/injection constrains and completion plan as a function of time.

3.1.1 Reservoir Model Overview

Figure 3-2: Grid Block Dimensions

Figure 3-3: Reservoir Model Overview

The field consists of a total of 77 wells placed on a 260i x 260j x 6k corner point grid. The anticline/syncline pair structure is surrounded by an aquifer that provides pressure support to the field. The field started production on January 1st of 1995 and ended production 22 years after on January 1st of 2017.

3.1.1.1 General Properties

The properties of the original model are summarized in Table 3-1:

Table 3-1: Original Model – Properties Overview

3.1.1.2 Original Map Files

The reservoir properties of the field, such as porosity, permeability, initial water saturation, and grid thickness distributions in each layer are presented below:

Figure 3-4: Porosity Map Files for All 6 Layers

The porosity distribution maps suggest that the porosity ranges between 0 and 20% across every layer.

Figure 3-5: Permeability, I (mD) Map Files in All 6 Layers

The permeability distribution across all layers is very low with most of the values ranging between 1mD and 150mD. The permeability distribution in the I-direction is equivalent to the permeability distribution in the J-direction.

Figure 3-6: Permeability, K (mD) Map Files in All 6 Layers

The permeability distribution in the vertical direction is the lowest ranging from 0mD to 140mD.

Figure 3-7: Initial Water Saturation Map Files for All 6 Layers

The initial water saturation remains constant throughout all 6 layers.

Figure 3-8: Grid Thickness (ft) Map Files for all 6 Layers

The thickness across the reservoir is constantly changing. However, the layers are thicker in the middle of the reservoir and thinner near the boundaries of the reservoir. Layers 4 and 5 are thinner throughout the entire layer compared to the remaining layers. Layers 1, 2 and 3 follow the same pattern.

3.1.2 Reservoir Characteristics

The reservoir is placed on top of a corner point grid system consisting of 260 grid blocks in both I and J directions.

The four corner grid blocks of the reservoir are depicted in Figure 3-9 with their respective centered coordinates.

The length and width of the reservoir are 14,365.05ft and 13,012.95ft respectively whereas the reservoir's thickness is constantly changing. See Figure 3-16.

Figure 3-9: Reservoir's Coordinates

A total of 27,600 grid blocks inherit aquifer property values adjacent to the sides of the reservoir. See the aquifer boundary effect in Figure 3-18. The remaining grid blocks located in the middle of the grid system represent other physical properties of the reservoir.

The rock compressibility is set at $2 * 10^{-6} psi^{-1}$ which encompasses a range of values representing the majority of consolidated sandstone and limestone data [23]. Moreover, the model does not include any specification of faults or geological units.

3.1.3 Components

The reservoir model is an under saturated reservoir that models the flow of oil, gas and water. The properties of each of the flowing components are specified in Table 3-2.

Table 3-2: Fluid Component Characteristics

Description	KEYWORD	Option	Value	Units
Reservoir Temperature	TRES	STO	130	°F
Oil Density	DENSITY OIL	Gas gravity (Air=1)	50.863	lb/ft ³
Gas Density	DENSITY/GRAVITY GAS		0.65	
Water Density	DENSITY WATER		62.01	lb/ft ³
Formation Volume Factor	BWI		1.01332	
Compressibility	CW		3.15E-06	1/psi
Reference Pressure for FVF	REFPW		14.696	psi
Viscosity	VWI		0.567336	cp
Pressure Dependence of CVW			0	psi

3.1.4 Rock Fluid Properties

An imbibition process is modeled by both water injection and incoming water from the aquifer. Theoretically, the water acts as a piston-like displacement to push the oil in the reservoir towards producing wells.

Figure 3-10: Relative Permeability Curves

Relative permeability curves describe the flowing conditions of oil, gas, and water as shown in Figure 3-10.

3.1.5 Initial Conditions

Initialization parameters such as initial reservoir saturation, water-oil contact, reference pressure and bubble point pressure are specified inside the numerical simulator.

The model has a bubble point pressure set at 1,500psi, suggesting that a two-phase envelope is likely to form at pressure values below the bubble point. Nevertheless, both the aquifer and water

injection assist the reservoir with enough pressure support to maintain a single phase flow. Only gas production is likely to take place at surface conditions.

3.1.6 Numerical Controls

The first and last simulation dates takes place in January 1st of 1995 and January 1st of 2017 respectively, suggesting a simulation of 22 years, 265 months or 8,036 days.

3.1.7 Wells and Recurrent

A total of 57 oil producers and 20 water injectors are drilled and perforated on January 1st of 1995 (first day of the simulation).

The well's location in the grid are shown in Figure 3-11 where the oil producers are placed in the middle of the reservoir (light green colored area) from the water injectors positioned inside the aquifer that borders the reservoir (blue area).

Figure 3-11: Well Locations on Initial Water Saturation Map

3.2 Modified Reservoir Model

The second section of this chapter elaborates on the modifications performed to the original reservoir with efforts to perform a more efficient numerical simulation that approaches real field behaviors. This step was conducted by restructuring the shape of the reservoir from a partial dome to an incline, reducing the number of geological, removing the aquifer boundary effect, adding operational constraints and workover events, and providing a strategic completion plan for each individual well.

3.2.1 Merging Layers

In order to reduce the computational work required for each of the tested simulation runs, the 6 original layers included in this model were combined into three layers. See *Figure 3-12* and *Figure 3-13* for comparison.

Figure 3-12: Original Model - 6 Geological Layers

Figure 3-13: Thesis Model - 3 Merged Geological Layers

Methodology:

This step was accomplished by opening the reservoir model inside the numerical simulator and editing the grid to combine the necessary layers into a single layer as shown in *Table 3-3*.

Table 3-3: Combining Layers Into Single Layer

<i>Original Model</i>		<i>Thesis Model</i>
Layer (K=1)	}	Layer (K=1)
Layer (K=2)		
Layer (K=3)		Layer (K=2)
Layer (K=4)		
Layer (K=5)		Layer (K=3)
Layer (K=6)		

3.2.2 Geological Restructuring

Figure 3-14: Stratigraphic Trap

Reservoir structures are dependent on the geometry of the rocks bounding the reservoir. In the case of the original model, both rock and aquifer properties were bounding the reservoir giving it the characteristics of an anticline/syncline pair (partial-dome).

The reservoir's geological structure was transformed from a partial dome to a stratigraphic trap. See the Figure 3-15 and Figure 3-16 for comparison.

Figure 3-15: Original Model –
Anticline/Syncline Pair

Figure 3-16: Thesis Model – Stratigraphic Trap

Methodology:

This step was accomplished by creating a new map file inside the numerical simulator. The new map file consisted of 2 important types of information: (1) a range of coordinates (X, Y) referencing a point in the grid system with (2) a corresponding depth for each data point. Figure 3-17 illustrates the X-Coordinates and Y-Coordinates for a total of 24 data points with their respective assigned depths. The 4 red highlighted values represent the corner points of the reservoir.

Figure 3-17: Thesis Grid Top Map File

3.2.3 Removing Aquifer Properties

The next step was to remove the aquifer boundary effect along the four sides of the reservoir. Notice in Figure 3-12 and Figure 3-13 aquifer property values near the sides of the reservoir create an aquifer boundary effect.

It was physically unrealistic to have an aquifer at the top of an stratigraphic trap considering the density difference between oil and water (Refer to Figure 3-14). Oil is less dense than water and therefore, it is unlikely to model a body of water at the top of the stratigraphic trap reservoir.

Methodology:

In order to remove the aquifer, the first step was to identify the grid blocks simulating an aquifer boundary effect along the four sides of the reservoir as shown in Figure 3-18. The first and last 30 grid blocks on both the I and J direction shown in color blue, represent the aquifer.

Figure 3-18: Aquifer Boundary Effect

The second step was to place a new $260i \times 260j$ grid on top of the reservoir property values of interest shown in white color in Figure 3-18. In order to only cover the white area from Figure 3-18, the grid block size was reduced from 50.25ft by 50.05ft to 42.50ft by 38.50ft.

This process is explained in more detail in Table 3-4. The number of grids multiplied by the grid size yields the length of the reservoir in both I and J directions. Since the properties of interest (excluding the aquifer property grid blocks) technically cover a $200i \times 200j$ grid as shown in the “Attempted Grid” row on the table, the length of the reservoir shrinks if the grid size is kept as the original. To keep the same number of grids as the original, the grid size is reduced, therefore, covering exactly the area with the reservoir property values of interest.

Table 3-4: Grid Modification Process

Grid	Orientation	No. Grids	Grid Size (ft)	Length (ft)
Original Grid	I direction	260	55.25	14,365.00
	J direction	260	50.05	13,013.00
Attempted Grid	I direction	200	55.25	11,050.00
	J direction	200	50.05	10,010.00
Final Grid	I direction	260	42.50	11,050.00
	J direction	260	38.50	10,010.00

Once the new grid was placed on top of the reservoir properties of interest, the third step was to export only the properties of interest as a *.msh file. Finally, the exported grid size was changed to the original size to keep the original dimensions of the reservoir model.

3.2.4 Modified Map Files

The modified map files (excluding the aquifer boundary effect) for a total of 3 layers are presented below with a constant initial water saturation set at 18% across the entire reservoir and a non-vertical communication established between layers by setting the permeability in the K direction equal to zero.

Figure 3-19: Thesis - Porosity Map Files

Figure 3-20: Porosity Distribution – 3 Layers

The porosity distribution in the first layer contains the largest number of grid blocks with the lowest porosity values while the third layer contains a larger number of grid blocks with higher porosity values.

Figure 3-21: Thesis - Permeability, I Map Files

Figure 3-22: Permeability (I, J direction) – 3 Layers

Most of the reservoir in all three layers has a very low permeability. However, some spots in the reservoir have higher permeability values between 200mD and 400mD. A smaller portion of the reservoir has values with the highest permeability ranging from 500mD to 1,000mD. The permeability histogram depicted in Figure 3-22.

Figure 3-23: Thesis - Permeability, K Map Files

Figure 3-24: Permeability (K-direction) – 3 Layers

The permeability in the vertical direction was assigned to zero to prevent any communication between layers.

Figure 3-25: Thesis - Initial Water Saturation Map Files

A simple averaging technique was performed to determine a value for the entire reservoir based on all three layers. Table 3-5 summarizes the field characteristics for each layer and for the entire reservoir.

Table 3-5: Field Characteristics

Attributes	Layer 1	Layer 2	Layer 3	Reservoir
Avg Porosity	6.67%	7.67%	11.95%	8.76%
Avg Permeability I, J	36.93 mD	49.14 mD	53.4 mD	46.49 mD
Avg Permeability K	0 mD	0 mD	0 mD	0 mD
Grid Thickness	1.71 ft - 282.98 ft	2.84 ft - 143.13 ft	10.78 ft - 184.45 ft	1.71 ft - 282.98 ft
Formation Depth	3829.72 ft - 4862.3 ft	3885.03 ft - 4971.53 ft	3913.6 ft - 4997.01 ft	3829.72 - 4997.01

3.2.5 Field Development

The development of the field consisted of a total of 7 phases. The first phase took place on January 1st of 1995 when a total of 5 oil producers were drilled and completed. A month later, February 2nd of 1995, 2 injectors were drilled and qualified for water injection. The remaining phases are shown in Table 3-6 below.

Table 3-6: Field Development Phases

Phases		Producers		Injectors	
		Wells	Dates	Wells	Dates
1	Phase 1	Wells 1 - 5	January 1, 1995	Injector 1 - 2	February 1, 1995
2	Phase 2	Wells 6 - 20	January 1, 1998	Injector 3 - 6	February 1, 1998
3	Phase 3	Wells 21 - 38	January 1, 2002	Injector 7 - 12	February 1, 2002
4	Phase 4a	Wells 39 - 42	January 1, 2007	Injector 13 - 14	February 1, 2007
5	Phase 4b	Wells 43 - 58	January 1, 2008	Injector 15 - 16	February 1, 2008
6	Phase 4c	Wells 49 - 52	January 1, 2009	Injector 17 - 18	February 1, 2009
7	Phase 4d	Wells 53 - 57	January 1, 2010	Injector 19 - 20	February 1, 2010

Figure 3-26: Field Development

3.2.6 Operational Constraints

In order to accommodate real-world situations, operating and monitoring constraints were enabled for both producers and injectors inside the numerical simulator. The constraints are described below:

Producers:

- Operating Constraints:
 - A minimum bottom-hole pressure was set at 1,700psi, slightly above the bubble point pressure, to keep a single-phase flow.
 - Wells were shut-in when the oil production was less than 30bbl/month.
- Monitoring Constraints:
 - A water cut constraint was used to control the amount of water produced. In real fields, reservoirs that use water injection as a driving mechanism for oil production take into consideration cost analyzes that are associated with the amount of water produced. The water cut was set at 90%, suggesting that wells with higher water production were shut-in.

Injectors:

- Operating Constraints:
 - A maximum bottom-hole pressure constraint was set at 4,000psi to prevent injectors from fracking the formation while providing enough pressure support and water supply [24].

3.2.7 Workover Events

Approaching reality through numerical simulation is a difficult task to do. Nevertheless, unexpected delays that often take place in a real field were added to the simulation by implementing shut-in events and reproducing bottom-hole pressure behaviors.

- Random shut-in events:

A series of daily and monthly random shut-in events were added to producing wells. Roughly 20% of the months and 15% of the days were non-productive for each of the existing producers. Water injectors, on the other hand, did not have any limitations as these were active in their respective development phases.

- Bottom-hole pressure fluctuations:

Bottom-hole pressure trends and fluctuations were mimicked in the simulation by randomly fluctuating the bottom-hole pressure trend on a daily and monthly basis within a range of 1,700psi – 1,900psi for all producers.

Table 3-7 summarizes the total number of times a well has been shut-in events and the total number of times that the bottom-hole pressure was altered. See “ALTER” and “SHUTIN “columns.

Table 3-7: Well Events

Well Name	EVENTS		
	SHUTIN	ALTER	TOTAL
Well-001	698	6,513	7,211
Well-002	631	6,445	7,076
Well-003	620	6,439	7,059
Well-004	473	5,000	5,473
Well-005	602	6,416	7,018
Well-006	446	4,630	5,076
Well-007	440	4,618	5,058
Well-008	445	4,576	5,021
Well-009	322	3,340	3,662
Well-010	451	4,701	5,152
Well-011	427	4,557	4,984
Well-012	424	4,578	5,002
Well-013	458	4,599	5,057
Well-014	464	4,842	5,306
Well-015	436	4,557	4,993
Well-016	293	3,059	3,352
Well-017	445	4,662	5,107
Well-018	439	4,520	4,959
Well-019	438	4,617	5,055
Well-020	435	4,586	5,021
Well-021	351	3,779	4,130
Well-022	378	3,892	4,270
Well-023	391	3,902	4,293
Well-024	352	3,685	4,037
Well-025	358	3,831	4,189
Well-026	381	3,955	4,336
Well-027	367	3,807	4,174
Well-028	386	3,996	4,382

Well Name	EVENTS		
	SHUTIN	ALTER	TOTAL
Well-029	388	3,983	4,371
Well-030	389	3,940	4,329
Well-031	380	3,889	4,269
Well-032	394	3,929	4,323
Well-033	385	4,006	4,391
Well-034	367	3,913	4,280
Well-035	372	3,901	4,273
Well-036	379	3,906	4,285
Well-037	381	3,836	4,217
Well-038	276	2,901	3,177
Well-039	277	2,913	3,190
Well-040	285	2,913	3,198
Well-041	281	2,911	3,192
Well-042	284	2,920	3,204
Well-043	258	2,645	2,903
Well-044	245	2,627	2,872
Well-045	206	2,242	2,448
Well-046	119	1,272	1,391
Well-047	246	2,633	2,879
Well-048	221	2,336	2,557
Well-049	232	2,338	2,570
Well-050	219	2,326	2,545
Well-051	228	2,335	2,563
Well-052	202	2,089	2,291
Well-053	196	2,059	2,255
Well-054	198	2,058	2,256
Well-055	198	2,059	2,257
Well-056	207	2,074	2,281
Well-057	195	2,059	2,254

3.2.8 Partial Completion Strategy:

The completion plan for each well was randomly assigned based on the phases at which each well was first introduced to the field. Figure 3-27 shows all the possible completion combinations.

Figure 3-27: Completion Combinations

Out of a total of 57 production wells, 16 wells were unproductive in the first and second layers while 14 wells were unproductive on the third layer. This suggests that 27% of the layers were unproductive.

A detailed completion timeline of the field is shown in Table 3-8. The green, orange and yellow columns represent the first, second, and third layers of the reservoir respectively. Each layer has a total of 3 columns. The first column contains the dates at which a layer was opened for production while the second column contains the dates at which a layer was closed due to a water cut or production constraint. The third column displays the period of time a layer was producing for. All wells are producing from at least one layer.

Table 3-8: Field Completion Plan

Well Name	Layer 1 OPEN	Layer 1 CLOSED	Production Time	Layer 2 OPEN	Layer 2 CLOSED	Production Time
Well-001	1-Jan-1995	1-Apr-2002	7 years and 3 months	X	X	UNPRODUCTIVE
Well-002	1-Jan-1995	1-Jan-2017	22 years	1-Jan-1998	1-Jan-2017	19 years
Well-003	X	X	UNPRODUCTIVE	1-Jan-1995	1-Jan-2017	22 years
Well-004	1-Jan-1995	1-Jan-2012	17 years	X	X	UNPRODUCTIVE
Well-005	1-Jan-1995	1-Feb-2014	19 years and 1 months	1-Jan-2001	1-Feb-2014	13 years and 1 months
Well-006	1-Jan-1998	1-Apr-2002	4 years and 3 months	1-Mar-2002	1-Apr-2002	1 month
Well-007	1-Jan-1998	1-Feb-1999	1 years and 1 months	X	X	UNPRODUCTIVE
Well-008	X	X	UNPRODUCTIVE	1-Jan-1998	1-Jan-2008	10 years
Well-009	1-Jan-1998	1-Feb-2009	11 years and 1 months	1-Jan-1998	1-Feb-2009	11 years and 1 months
Well-010	1-Jan-1998	1-Jan-2017	19 years	X	X	UNPRODUCTIVE
Well-011	1-Jan-1998	1-Jan-2004	6 years	1-Jan-2000	1-Jan-2004	4 years
Well-012	1-Jan-1998	1-Mar-2000	2 years and 2 months	1-Jan-1998	1-Mar-2000	2 years and 2 months
Well-013	1-Jan-1998	1-Jan-2017	19 years	X	X	UNPRODUCTIVE
Well-014	1-Jan-1998	1-Apr-2008	10 years and 3 months	1-Jan-1998	1-Apr-2008	10 years and 3 months
Well-015	X	X	UNPRODUCTIVE	1-Jan-2002	1-Jan-2017	15 years
Well-016	X	X	UNPRODUCTIVE	1-Jan-1999	1-Apr-2001	2 years and 3 months
Well-017	X	X	UNPRODUCTIVE	1-Jan-1998	1-Jan-2017	19 years
Well-018	X	X	UNPRODUCTIVE	1-Jan-1998	1-Jul-1998	6 months
Well-019	1-Jan-1999	1-Jan-2017	18 years	X	X	UNPRODUCTIVE
Well-020	1-Jan-1999	1-Aug-2011	12 years and 7 months	1-Jan-1999	1-Aug-2011	12 years and 7 months
Well-021	1-Jan-2002	1-May-2010	8 years and 4 months	X	X	UNPRODUCTIVE
Well-022	1-Jan-2002	1-Jan-2017	15 years	X	X	UNPRODUCTIVE
Well-023	1-Jan-2002	1-Jan-2017	15 years	X	X	UNPRODUCTIVE
Well-024	1-Jan-2002	1-Jan-2017	15 years	1-Jan-2002	1-Jan-2017	15 years
Well-025	1-Jan-2002	1-Jan-2017	15 years	X	X	UNPRODUCTIVE
Well-026	X	X	UNPRODUCTIVE	1-Jan-2008	1-Jul-2009	1 year and 6 months
Well-027	1-Jan-2002	1-Jan-2017	15 years	X	X	UNPRODUCTIVE
Well-028	X	X	UNPRODUCTIVE	1-Jan-2002	1-Jan-2005	3 years
Well-029	X	X	UNPRODUCTIVE	1-Jan-2002	1-Jul-2015	13 years and 6 months
Well-030	1-Jan-2002	1-Apr-2011	9 years and 3 months	1-Jan-2002	1-Apr-2011	9 years and 3 months
Well-031	1-Jan-2002	1-Jan-2017	15 years	1-Jan-2002	1-Jan-2017	15 years
Well-032	1-Jan-2002	1-Dec-2016	14 years and 11 months	1-Jan-2002	1-Dec-2016	14 years and 11 months
Well-033	1-Jan-2004	1-Nov-2007	3 years and 10 months	1-Jan-2002	1-Nov-2007	5 years and 10 months
Well-034	1-Jan-2002	1-Jan-2017	15 years	1-Jan-2005	1-Jan-2017	12 years
Well-035	1-Jan-2004	1-Mar-2015	11 years and 2 months	1-Jan-2002	1-Mar-2015	13 years and 2 months
Well-036	X	X	UNPRODUCTIVE	1-Jan-2002	1-Jan-2017	15 years
Well-037	X	X	UNPRODUCTIVE	1-Jan-2002	1-May-2013	11 years and 4 months
Well-038	X	X	UNPRODUCTIVE	1-Jan-2007	1-Jan-2017	10 years
Well-039	1-Jan-2007	1-Jan-2017	10 years	1-Jan-2007	1-Jan-2017	10 years
Well-040	1-Jan-2007	1-Jan-2017	10 years	X	X	UNPRODUCTIVE
Well-041	1-Jan-2007	1-Jan-2017	10 years	X	X	UNPRODUCTIVE
Well-042	1-Jan-2007	1-Jan-2017	10 years	1-Jan-2007	1-Jan-2017	10 years
Well-043	1-Jan-2008	1-Jan-2017	9 years	1-Jan-2014	1-Jan-2017	3 years
Well-044	1-Jan-2008	1-Jan-2017	9 years	1-Jan-2008	1-Jan-2017	9 years
Well-045	1-Jan-2008	1-Aug-2015	7 years and 7 months	1-Jan-2008	1-Aug-2015	7 years and 7 months
Well-046	1-Jan-2008	1-Jan-2012	4 years	1-Jan-2008	1-Jan-2012	4 years
Well-047	X	X	UNPRODUCTIVE	1-Jan-2008	1-Jan-2010	2 years
Well-048	1-Jan-2012	1-Jan-2017	5 years	X	X	UNPRODUCTIVE
Well-049	X	X	UNPRODUCTIVE	X	X	UNPRODUCTIVE
Well-050	1-Jan-2009	1-Jan-2017	8 years	X	X	UNPRODUCTIVE
Well-051	X	X	UNPRODUCTIVE	1-Jan-2009	1-Jan-2010	1 year
Well-052	1-Jan-2009	1-Apr-2016	7 years and 3 months	1-Jan-2009	1-Apr-2016	7 years and 3 months
Well-053	1-Jan-2010	1-Jan-2017	7 years	1-Jan-2010	1-Jan-2017	7 years
Well-054	1-Jan-2010	1-Jan-2017	7 years	1-Jan-2010	1-Jan-2017	7 years
Well-055	1-Jan-2010	1-Jan-2017	7 years	1-Jan-2010	1-Jan-2017	7 years
Well-056	X	X	UNPRODUCTIVE	1-Jan-2010	1-Jan-2017	7 years
Well-057	1-Jan-2010	1-Jan-2017	7 years	1-Jan-2010	1-Jan-2017	7 years
Unproductive	16 Wells			16 Wells		

Well Name	Layer 3 OPEN	Layer 3 CLOSED	Production Time
Well-001	X	X	UNPRODUCTIVE
Well-002	X	X	UNPRODUCTIVE
Well-003	1-Jan-1995	1-Jan-2017	22 years
Well-004	X	X	UNPRODUCTIVE
Well-005	1-Jan-2006	1-Feb-2014	8 years and 1 month
Well-006	1-Mar-2002	1-Apr-2002	1 month
Well-007	X	X	UNPRODUCTIVE
Well-008	1-Jan-1999	1-Jan-2008	9 years
Well-009	1-Jan-1998	1-Feb-2009	11 years and 1 month
Well-010	1-Jan-1998	1-Jan-2017	19 years
Well-011	X	X	UNPRODUCTIVE
Well-012	1-Jan-1998	1-Mar-2000	2 years and 2 months
Well-013	X	X	UNPRODUCTIVE
Well-014	X	X	UNPRODUCTIVE
Well-015	1-Jan-1998	1-Jan-2017	19 years
Well-016	1-Jan-1998	1-Apr-2001	3 years and 3 months
Well-017	1-Jan-1998	1-Jan-2017	19 years
Well-018	1-Jan-1998	1-Jul-1998	6 months
Well-019	X	X	UNPRODUCTIVE
Well-020	1-Jan-1999	1-Aug-2011	12 years and 7 months
Well-021	1-Jan-2005	1-May-2010	5 years and 4 months
Well-022	1-Jan-2004	1-Jan-2017	13 years
Well-023	1-Jan-2005	1-Jan-2017	12 years
Well-024	X	X	UNPRODUCTIVE
Well-025	1-Jan-2002	1-Jan-2017	15 years
Well-026	1-Jan-2002	1-Jul-2009	7 years and 6 months
Well-027	X	X	UNPRODUCTIVE
Well-028	X	X	UNPRODUCTIVE
Well-029	1-Jan-2002	1-Jul-2015	13 years and 6 months
Well-030	X	X	UNPRODUCTIVE
Well-031	1-Jan-2002	1-Jan-2017	15 years
Well-032	1-Jan-2002	1-Dec-2016	14 years and 11 months
Well-033	1-Jan-2002	1-Nov-2007	5 years and 10 months
Well-034	1-Jan-2010	1-Jan-2017	7 years
Well-035	1-Jan-2002	1-Mar-2015	13 years and 2 months
Well-036	1-Jan-2002	1-Jan-2017	15 years
Well-037	1-Jan-2011	1-May-2013	2 years and 4 months
Well-038	1-Jan-2007	1-Jan-2017	10 years
Well-039	1-Jan-2007	1-Jan-2017	10 years
Well-040	1-Jan-2007	1-Jan-2017	10 years
Well-041	X	X	UNPRODUCTIVE
Well-042	X	X	UNPRODUCTIVE
Well-043	1-Jan-2015	1-Jan-2017	2 years
Well-044	1-Jan-2008	1-Jan-2017	9 years
Well-045	1-Jan-2008	1-Aug-2015	7 years and 7 months
Well-046	1-Jan-2008	1-Jan-2012	4 years
Well-047	1-Jan-2008	1-Jan-2017	9 years
Well-048	1-Jan-2009	1-Jan-2017	8 years
Well-049	1-Jan-2009	1-Jan-2017	8 years
Well-050	1-Jan-2009	1-Jan-2017	8 years
Well-051	1-Jan-2009	1-Jan-2017	8 years
Well-052	1-Jan-2009	1-Apr-2016	7 years and 3 months
Well-053	1-Jan-2010	1-Jan-2017	7 years
Well-054	1-Jan-2010	1-Jan-2017	7 years
Well-055	1-Jan-2010	1-Jan-2017	7 years
Well-056	1-Jan-2010	1-Jan-2017	7 years
Well-057	1-Jan-2010	1-Jan-2017	7 years
Unproductive	14 Wells		

3.3 Available Data

The total oil, gas, and water production of the field was 6,223,078.25bbl, 2,597,680.627.59scf, and 3,399,965.94bbl respectively.

Table 3-9: Field Production

Field Production		
Rate	Value	Units
Oil	6,223,078.25	bbl
Gas	2,597.68	mmscf
Water	3,399,965.94	bbl

Individual cumulative oil production ranged from as high as 650,000bbl to as low as 2,000bbl. Cumulative gas production ranged from 270,000mscf to 800mscf and cumulative water production ranged from 660,000bbl to 500bbl.

Table 3-10: Cumulative Production Statistics on a Well Basis

Rate	High	Average	Low
Oil (bbl)	650,000	110,000	2,000
Gas (mmscf)	270	45	0.8
Water (bbl)	660,000	60,000	500

Figure 3-28 illustrates the different format options in which data can be retrieved to an Excel Spreadsheet. For example, “Well” data is available for a total of 77 wells. Each well contains data for a total of 60 different attributes (See “Data Selection” Figure 3-28). “Layered” data is available for a total of 231 layers (77 wells x 3 layers). Each layer contains data for a total of 50 different attributes. “Special History” data, is available for a total of 3 attributes (Reservoir pressure, oil saturation and water saturation) at grid block locations including the well center grid block (1 WBA) and the surrounding grid blocks (8 WBA) in all 3 layers, resulting in a total of 6,238 data points. Moreover, each of the selected properties can be exported on a yearly, quarterly, monthly, or a daily basis as shown in the *Report Period* tab on the bottom-left corner of Figure 3-28.

Format

☐ Single Table

☒ Multiple Tables Worksheet: File, Table: Property, Row: Time, Column: Well

Property 1

Time	Date	Well 1	Well 2	Well 3	Other Wells
xxx	yyyy-mm-dd hh:mm:ss	xxx.xx	xxx.xx	xxx.xx	
...	...	...	...	...	
xxx	yyyy-mm-dd hh:mm:ss	xxx.xx	xxx.xx	xxx.xx	

Other Properties

file1.sr3 file2.sr3 Other Data Sources →

Data Sources

Yvon Model.sr3

Data Selection

REPORT DATA	NAMES	PROPERTIES
☐ Wells	☐ Custom (0 of 77)	☐ Custom (0 of 60)
☒ Layers	☒ Default (231 of 231)	☒ Default (1 of 50)
☐ Groups	☐ Custom (0 of 2)	☐ Custom (0 of 56)
☐ Sectors	☐ Custom (0 of 1)	☐ Custom (0 of 47)
☐ Special History	☐ Custom (0 of 1)	☐ Default (0 of 6238)
☐ Block Properties	☐ Custom (0 of 0)	☐ Default (0 of 39)

Report Period

☐ Yearly ☐ Quarterly ☒ Monthly ☐ Daily ☐ All Well Times

Export to Excel Close

Figure 3-28: Reservoir Simulation Outputs

Below are brief descriptions of the data available for retrieval.

1. Wells: provides data for every well from the date the well is completed until the date the well is abandoned. Approximately 40 attributes options are available for data analysis. See Table 3-11.

Table 3-11: Well Based Reported Data

Wells Reported Data				
Cumulative Bottom Hole Fluid	Bottom Hole Fluid Rate	Gas Oil Ratio	On Time Fraction	Well BHP Derivative
Cumulative Gas Oil Ratio	Fluid Rate	Gas Water Ratio	Period Gas Production	Well Block Pres. Derivative
Cumulative Gas	Gas Rate	Oil Gas Ratio	Period Oil Production	Well Block Pressure
Cumulative lift gas injected	Lift Gas Rate	Water Gas Ratio	Period Water Production	Well Bottom-hole Pressure
Cumulative Liquid	Liquid Rate	Water Oil Ratio	Well Cumulative Open On-time	Well Head Pres. Derivative
Cumulative Oil	Oil Rate	Oil Cut	Well Open Fraction	Well Head Pressure
Cumulative Water Mass	Water Mass Rate	Water Cut	Well Operating Mode	Well Mobility - Weighted Block P
Cumulative Water	Water Rate		Well State	Well Mobility - Weighted Datum Pressure
Cumulative Water Oil Ratio				

2. Layer Based Data: provides data for every well at every layer from the date the well is completed until the date the well is abandoned.

Table 3-12: Layer Based Reported Data

Layers Reported Data				
Cumulative Bottom Hole Fluid	Bottom Hole Fluid Rate	Gas Oil Ratio	On Time Fraction	Well Block Pres. Derivative
Cumulative Gas Oil Ratio	Fluid Rate	Gas Water Ratio	Period Gas Production	Well Block Pressure
Cumulative Gas	Gas Rate	Oil Gas Ratio	Period Oil Production	Well Pressure
Cumulative Liquid	Liquid Rate	Water Gas Ratio	Period Water Production	Well Pressure Derivative
Cumulative Oil	Oil Rate	Water Oil Ratio	Status (0 = Open , 1 = closed , 2 = auto)	
Cumulative Water Mass	Water Mass Rate	Oil Cut	Well Cumulative Open On-time	
Cumulative Water	Water Rate	Water Cut	Well Open Fraction	
Cumulative Water Oil Ratio			Well Operating Mode	
			Well State	

3. Special History: provides data for every specified grid block location from the beginning of the simulation until the end of the simulation. The specified grid block locations and the properties of interest must be provided prior to running the simulation.

Table 3-13: Special History Reported Data

Special History Reported Data
Oil Saturation
Water Saturation
Pressure

4. Block Properties: provides data for a specific grid block location by specified by the user. This information can be accessed after running the simulation.

Table 3-14: Block Properties Reported Data

Block Properties Reported Data			
Gas Saturation	Krg at Connate Liquid (2)	Low Side Trans Multiplier I	Gas per unit area - Layer
Oil Saturation	Kro at Connate Water ST	Low Side Trans Multiplier J	Gas per unit area - Total
Water Saturation	Krw at Connate Gas (2)	Low Side Trans Multiplier K	Oil per unit area - Layer
Grid Bottom	Krw at Connate Gas (2)	Max Gas-Oil Cap Pres	Oil per unit area - Total
Grid Centroid X	Krw at Irreducible Oil ST	Max Water-Oil Cap Pres	Net Pay
Grid Centroid Y	Permeability I	Water Cap Pres Shift/Offset	Net Pore Volume
Grid Paydepth	Permeability J	Gross Block Volume	Net to Gross Ratio
Grid Thickness	Permeability K	Modified Block Volume	
Grid Top	Trans Multiplier I		
	Trans Multiplier J		
	Trans Multiplier K		

CHAPTER 4

4 DATA-DRIVEN RESERVOIR MODELING

This chapter is dedicated to the development of five TDM models using IMagine. IMagine is a software that implements artificial intelligence techniques, such as artificial neural networks, genetic algorithms and fuzzy logic to solve oil and gas industry related problems [25].

TDM models were built using data generated from the numerical reservoir model described in section 3.2 to history match and forecast production, reservoir pressure, and water saturation output attributes.

The development and analysis of a TDM consist of the following phases:

1. Data preparation
2. Data import
3. Static modeling
4. Top-down modeling

The first phase focuses on the details of data collection, data cleansing, and data preparation with efforts to properly import formatted and pre-processed data into IMagine.

The second phase briefly mentions the steps taken to successfully import well-based and production rate data into the software.

The third phase elaborates on the pre-modeling analysis that characterizes the reservoir [25].

The fourth phase defines a total five predictive data-driven models that are interconnected in the following order: oil rate, gas rate, water rate, reservoir pressure and water saturation. Figure 4-1 illustrates the order in which the predictive models are presented.

Figure 4-1: Top-Down Model Levels

4.1 Data Preparation

Well-based and production rate data were imported into IMagine. The well-based data is further classified into static and dynamic datasets. The formatting of each dataset is explained in detail in the following section.

4.1.1 Data Formatting

In the data preparation process, information was arranged in standardized tabular formats. The static dataset was organized with columns representing static properties and rows representing all

the wells in the field (producers and injectors). A single static file (*.csv) was enough to provide all the static information regarding the reservoir. An example of the static file imported into the software is shown in Figure 4-2.

On the other hand, one dynamic dataset constituted the values of a single property that changed over time. All dynamic properties were saved in separate *.csv files with a common formatting structure depicted in Figure 4-3, where columns represent a series of dates and rows represent all the wells.

		Columns ~ Static Properties								
		Well Name	Well Type	Top	TVD	Initial water Saturation	Grid Thickness	Permeability	Porosity	Completion Footage
Rows ~ Wells		Well-001	P							
		Well-002	P							
		Well-003	P							
		Well-004	P							
		Well-005	P							
		:								
		Well-057	P							
		Injector-001	I							
		Injector-002	I							
		Injector-003	I							
		Injector-004	I							
		Injector-005	I							
		:								
		Injector-020	I							

Figure 4-2: Static Dataset Format

		Dates ~ Fomat: m/d/yyyy							
	Well Name	12 / 31 / 1994	1 / 31 / 1995	2 / 28 / 1995	3 / 30 / 1995	...	10 / 31 / 2016	11 / 31 / 2016	12 / 31 / 2016
Rows ~ Wells	Well-001								
	Well-002								
	Well-003								
	Well-004								
	Well-005								
	:								
	:								
	Well-056								
	Well-057								

Figure 4-3: Dynamic Dataset Format

4.1.2 Data Collection

The data collected from the numerical simulation results output file contained static, dynamic and production rate data as previously mentioned in section 3.3.

4.1.2.1 Static Data

Static properties were exported as text files, cleansed and transformed into the required table format by means of Python coding (See Figure 4-2). As the simulation data was exported per layer, it was necessary to average the reservoir properties with respect to the open layers in order to determine one value per well. A single value was provided for each well to meet the formatting requirements on a well basis rather than a layer basis. This was accomplished by using the weight average method with respect to grid thickness (See Eq. 4-3). Furthermore, the top and TVD values from each well were selected according to the upper most open layer and the lower most open layer. In a similar fashion, completion footage was calculated with respect to the grid thickness of completed layers.

Figure 4-4 illustrates the static file imported in the final spatio-temporal database.

Well Name	Well Type	X	Y	Top (ft)	TVD (ft)	Swi (%)	Thickness (ft)	Permeability I (mD)	Permeability J (mD)	Permeability K (mD)	Porosity (%)	Completion (ft)
Well-001	P	20,829.25	10,610.60	4,004.90	4,211.24	18.0	206.34	36.43	36.43	-	11.18	98.90
Well-002	P	13,812.50	10,810.80	4,349.40	4,523.80	18.0	278.49	97.16	97.16	-	9.99	174.41
Well-003	P	17,901.00	14,414.40	4,207.09	4,463.09	18.0	351.18	24.37	24.37	-	12.74	256.00
Well-004	P	13,425.75	16,616.60	4,359.73	4,501.79	18.0	270.32	8.59	8.59	-	6.45	142.06
Well-005	P	20,774.00	17,567.55	4,008.85	4,168.94	18.0	160.09	73.74	73.74	-	13.57	160.09
Well-006	P	12,486.50	17,467.45	4,414.25	4,522.52	18.0	203.63	22.14	22.14	-	7.11	108.28
Well-007	P	11,436.75	12,412.40	4,451.80	4,668.08	18.0	355.62	113.65	113.65	-	12.26	216.28
Well-008	P	12,155.00	18,868.85	4,446.39	4,497.73	18.0	74.79	201.27	201.27	-	12.36	51.34
Well-009	P	13,536.25	18,418.40	4,364.87	4,483.22	18.0	118.35	6.72	6.72	-	5.06	118.35
Well-010	P	21,050.25	14,264.25	3,983.99	4,191.32	18.0	207.33	18.42	18.42	-	9.83	160.33
:						0.0				-		
:						0.0				-		
Injector-001	I	10,221.25	17,517.50	4,498.05	4,687.33	18.0	189.28	524.22	524.22	-	15.33	-
Injector-002	I	9,945.00	12,462.45	4,512.25	4,866.24	18.0	353.99	259.46	259.46	-	12.61	-
Injector-003	I	10,497.50	19,619.60	4,516.81	4,556.03	18.0	39.23	7.77	7.77	-	4.72	-
Injector-004	I	20,221.50	9,459.45	4,020.33	4,286.60	18.0	266.27	38.61	38.61	-	12.60	-
Injector-005	I	22,652.50	18,568.55	3,963.58	4,128.50	18.0	164.92	5.46	5.46	-	7.28	-
Injector-006	I	14,365.00	20,820.80	4,297.07	4,380.93	18.0	83.86	55.67	55.67	-	6.95	-
Injector-007	I	13,923.00	9,309.30	4,322.86	4,615.16	18.0	292.29	12.05	12.05	-	8.36	-
Injector-008	I	23,205.00	14,864.85	3,846.95	4,021.04	18.0	174.09	25.10	25.10	-	10.23	-
Injector-009	I	17,459.00	9,759.75	4,141.38	4,490.02	18.0	348.64	40.67	40.67	-	14.07	-
Injector-010	I	18,177.25	20,570.55	4,103.18	4,253.32	18.0	150.15	3.13	3.13	-	4.36	-
:										-		
:										-		

Figure 4-4: Formatted Static Data

A visual representation of the static data and the retrieving process is shown in Figure 2-1.

Figure 4-5: Wellbore Diagram

The *Grid Block Table* presented in Figure 4-5 contains information illustrated in the diagram to the left of the table. The “Block UBA” column provides information regarding well location (X, Y, Z Coordinates). The second column “Perf Type” provides completion information. If a layer is completed it is denoted as “OPEN” and is colored in light blue in the well trajectory diagram shown in Figure 4-5. The top and bottom depths of each layer are provided in the “TVD Entry (ft)” and “TVD Exit (ft)” columns respectively. The thickness of each layer is calculated by taking the difference between the top and bottom depths of any layer.

A diagram for each well is provided with well location and trajectory, well type, top and bottom of the formation, top and bottom of each layer, completion, grid thickness and more. Porosity, permeability, initial water saturation and other property values were available in a text file format at each grid block.

4.1.2.2 Dynamic Data

After examining all the potential information available for the development of a data-driven model, it was concluded that the most meaningful data was found in the layered and the special history report formats presented in Figure 3-28. The main reason for retrieving data on a layer basis was the nature of the partial completion plan implemented in the numerical reservoir simulation.

Both layered and special history formats are described below:

1. **Special History:** contains data for all the simulation time steps (January 1st, 1995 – January 1st, 2017).
 - Oil Saturation (fraction)
 - Water Saturation (fraction)
 - Reservoir pressure (psi)
2. **Layer Based:** contains data only for time steps a well produces. The life of a well is determined by a minimum production constraint and a maximum water cut percentage.
 - Oil production rate (bbl/month)
 - Gas production rate ($ft^3/month$)
 - Water production rate (bbl/month)
 - Well block pressure (psi) – Reservoir pressure (psi)
 - Well pressure (psi) – Flowing bottom-hole pressure (psi)

Figure 4-6 illustrates the format structure of the exported data while Figure 4-3 shows the required table format for the generation of a well-constructed spatio-temporal database.

Figure 4-6: Primary Data Exporting Formats

Moreover, static properties such as porosity and permeability changed as a function of time and were therefore formatted and included into the dynamic dataset.

4.1.3 Data Cleansing

Erroneous or incomplete data impacts the learning process during the development of predictive models.

After inspecting the layer based and special history data exported, misleading values, such as negative or exponentially small numbers, were encountered in oil, gas, and water production datasets at random timesteps. Such values were replaced with zeros if the well continued to produce and if the layer was completed.

A secondary cleaning procedure was based on oil production. When oil production was zero, it was important to communicate to the neural network that there was no gas and/or water production. Therefore, at timesteps where oil production was zero, gas and water production were set to zero accordingly.

Due to the fact that the data was exported on a layer basis, it was necessary to bring the data back to a well basis as this was the required format for the recreation of the spatio-temporal database

earlier described in section 4.1.1. Simple average of completed and productive layers was not an accurate approach to communicate the contribution of fluid flow through porous media to the neural network. For reservoir properties a weighted average method was determined by permeability and thickness. Flowing bottom-hole pressure was weight averaged on thickness.

The impact of using a weight average against a simple average is explained in Figure 4-7.

Simple average:

$$P_r = \frac{P_{r1} + P_{r2} + P_{r3}}{3}$$

$$P_r = \frac{3,560 + 1,320 + 2,380}{3}$$

$$P_r = 2,420psi$$

Weighted Average:

$$P_r = \frac{P_{r1} * (h_1 * k_1) + P_{r2} * (h_2 * k_2) + P_{r3} * (h_3 * k_3)}{(h_1 * k_1 + h_2 * k_2 + h_3 * k_3)}$$

$$P_r = \frac{3,560 * (58 * 14) + 1,320 * (8 * 2) + 2,380 * (28 * 7)}{(58 * 14 + 8 * 2 + 28 * 7)}$$

$$P_r = \frac{3,378,320}{1,024}$$

$$P_r = 3,299.14psi$$

Figure 4-7: Simple Average Methods vs Weight Average Method Example

In summary:

- Well production was the summation of the production from all layers.

$$Well\ Production = Production_{L1} + Production_{L2} + Production_{L3} \quad Eq. 4-1$$

- Reservoir properties, including porosity, permeability, and reservoir pressure, were weight averaged based on KH (permeability and thickness)

$$(Property)_{Avg} = \frac{Prop_{L1} * (K_{L1} * H_{L1}) + Prop_{L2} * (K_{L2} * H_{L2}) + Prop_{L3} * (K_{L3} * H_{L3})}{((K_{L1} * H_{L1}) + (K_{L2} * H_{L2}) + (K_{L3} * H_{L3}))} \quad \text{Eq. 4-2}$$

- Surface properties, including flowing bottom-hole pressure, were weight averaged based on H (thickness).

$$(Property)_{Avg} = \frac{Prop_{L1} * (H_{L1}) + Prop_{L2} * (H_{L2}) + Prop_{L3} * (H_{L3})}{((H_{L1}) + (H_{L2}) + (H_{L3}))} \quad \text{Eq. 4-3}$$

4.2 Data Import

Importing well-based and production rate data was the first step in the recreation of a final spatio-temporal database to be used in the development of predictive data-driven models.

The arrangement of the final database imported into IImagine with all static, dynamic and production rate data is depicted in Figure 4-8.

Figure 4-8: Spatio-temporal Database

The total number of static, dynamic, and production attributes was 12, 10 and 3 respectively. Dynamic and production data was provided on a monthly basis encompassing a total of 265 months starting in January 1st of 1995 and ending in January 1st of 2017.

4.3 Static Modeling

Static modeling focuses on efficiently performing pre-modeling analysis with efforts to map and define the reservoir. This is accomplished by defining the grid and boundary of the reservoir, performing spatial interpolation to assign reservoir property values to the entire grid system, and by performing volumetric and geostatistic calculations.

4.3.1 Grid and Boundary

The grid area was set as 5 acres. The boundary of the reservoir was drawn as closely as possible to the boundary of the numerical reservoir model (See Figure 4-9).

Figure 4-9: Grid and Boundary

4.3.2 Geostatistics

In this module, reservoir properties at each grid block were populated based on the values provided at each well location. Inverse distance weighting method was the preferred interpolation technique used to generate distribution maps for both static and dynamic properties imported into the software.

Figure 4-10: Static and Dynamic Spatial-Interpolation Using Inverse Distance Weighting Method

4.3.3 Reservoir Delineation

In this module, effective drainage was determined for each well in the reservoir.

Figure 4-11: Reservoir Delineation using Voronoi Technique

4.3.4 Volumetric

Volumetric and geostatistic calculations were performed using reservoir property values previously determined in section 4.3.2. These calculations are necessary to fill information that was not previously imported, such as initial oil in place, initial gas in place, temperature, saturations, etc.

4.4 Top-Down Modeling

Top-down models are often composed of one or more interconnected predictive models that are history matched and deployed under different operational conditions.

Two datasets are often used in top-down reservoir modeling:

1. Development dataset
2. Deployment dataset

The development dataset partially or entirely uses available data to train, calibrate and validate the model through the application of artificial neural networks. The “development” is also referred to as history match. Once the TDM model is validated in time, it can be used for forecasting purposes. This is also referred to as the deployment dataset which includes time ranges beyond the development dataset [17]. Figure 4-12 illustrates an example of development and deployment time ranges.

Figure 4-12: Top-Down Modeling – History Match and Forecast

Due to the lack of data beyond January 1st of 2017, validation of the TDM’s forecast was not possible. However, forecasting was performed on data ranges where TDM predictions could be compared against the numerical simulation data.

4.4.1 Build and History Match

A total of five different TDM models were built with efforts to history match oil, gas, and water production, reservoir pressure and water saturation distributions. Only two TDM models were further deployed on a blind dataset to evaluate their forecast performance.

Each TDM model was characterized by the partitioning type implemented, the input attributes used in the neural network development, and the number of records used in the training, calibration, and validation datasets.

The first TDM implemented a random partitioning approach. Due to the nature of the partitioning method used, the model had the lowest degree of confidence. The second TDM was built using a mixed partitioning method in which the last year (January 1st, 2016 – January 1st, 2017) of the development dataset was used as a blind history match. The third TDM resembled the partitioning type from the second scenario. However, the last 2 years (January 1st, 2015 – January 1st, 2017) of the development dataset were used as a blind history match. The fourth TDM performed 1 year of blind history-matching (January 1st, 2015 – December 31st, 2015) and 1 year of forecasting (January 1st, 2016 – January 1st, 2017). The fifth TDM performed 1 year of blind history matching (January 1st, 2014 – December 31st, 2014) and 2 years of forecasting (January 1st, 2015 – January 1st, 2017).

Table 4-1 briefly summarizes each of the scenarios to be discussed in more detail. “MP” and “RP” are abbreviations for “Mixed Partitioning” and “Random Partitioning” respectively. “1V”, “2V” are short for “1-year validation” and “2-year validation” while “1F” and “2F” refer to “1-year forecast” and “2-year forecast” respectively.

Table 4-1: History Match and Forecast Scenarios – Description

Scenario	Name	Partitioning	Training	Calibration	Validation	Forecast
1	RP TDM	Random	80%	10%	10%	-
2	MP TDM 1V	Mixed	80%	20%	1 Year	-
3	MP TDM 2V	Mixed	80%	20%	2 Years	-
4	MP TDM 1V 1F	Mixed	80%	20%	1 year	1 Year
5	MP TDM 1V 2F	Mixed	80%	20%	1 year	2 Years

Each TDM model built will be described into detail in the following sections.

4.4.1.1 Scenario 1 – Random Partitioning TDM

The first scenario was conducted to test the most basic partitioning approach while sacrificing the robustness and degree of confidence of the model.

Data-Driven Dataset Generation:

The TDM model incorporated five interconnected data-driven models previously discussed and illustrated in Figure 4-1. The development and deployment datasets consisted of the same time ranges, from January 1st of 1995 until January 1st of 2017, suggesting that no forecasting was performed.

Figure 4-13: Scenario 1 - Development Dataset

Data-driven datasets for each predictive model were generated by including candidate attributes from the focal well, 2 offset producers, and 2 offset injectors (neighboring information was included to account for the influence of production and water injection with respect to the focal well).

Attribute selection for both focal and offset wells was performed at different timesteps where the current and previous timestep were denoted as “t” and “t-1” respectively. The model output was to be predicted at time “t” based on previous information at timesteps of “t-1”. However, a set of operational conditions determines the outcome of the model output. Therefore, operational conditions such as completion, flowing bottom-hole pressure, and water injection were provided at the current timestep of “t”.

Once the development and deployment datasets were established and all candidate attributes were selected at their respective timesteps, oil, gas, water, reservoir pressure and water saturation data-driven datasets were compiled, cleansed based on zero oil production at the timestep of “t” and sorted in chronological order.

Data-Driven Model Development:

Data-driven modeling uses artificial neural networks to build well-trained predictive models capable of learning from data and predicting possible outcomes.

Figure 4-14: Neural Network Data Preparation – Oil Model

Each data-driven dataset was further compiled into a spatio-temporal database by reducing the number of attributes to be used in the neural network development (KPI analysis was used as a guiding tool to identify the most influential attributes on the output attributes (APPENDIX B: Key Performance Indicators)). Figure 4-14 illustrates an example input attributes used to predict an output value.

Figure 4-15 shows the input attributes included in the neural network development of each data-driven model.

Scenario 1 – TDM Input Attributes

Oil Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(1I)	91
2	Porosity (%)	90	3	Top (ft)(1I)	90
3	TVD (ft)	52	5	TVD (ft)(1I)	73
8	Pay Thickness (ft)	23	6	Top (ft)(2P)	65
4			9	TVD (ft)(1P)	55
Dynamic Attributes			10	X/Longitude(1P)	52
1	Oil Rate (t-1)	100	11	Pay thickness (ft)(1P)	50
2	Gas Rate (t-1)	100	7		
3	Permeability I(t-1)	49	Dynamic Attributes		
4	Time	48	1	FBH Pressure (psi)(t)(1I)	100
4			2	Distance(t-1)(2P)	97
TOTAL ATTRIBUTES			3	FBH Pressure (psi)(t-1)(1I)	96
25			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Gas Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
Dynamic Attributes			4	X/Longitude(1I)	84
1	Oil Rate (t)	100	5	TVD (ft)(1I)	73
2	Oil Rate (t-1)	60	8	Y/Latitude(1I)	56
3	Gas Rate (t-1)	60	6		
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
TOTAL ATTRIBUTES			2	Distance(t-1)(2P)	97
22			3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Water Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
2	X/Longitude	89	1	X/Longitude(2P)	100
3	Top (ft)	84	2	Top (ft)(2P)	90
9	Porosity (%)	1	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
Dynamic Attributes			5	X/Longitude(2I)	75
1	Water Rate (t-1)	100	7	TVD (ft)(2I)	65
2	Oil Saturation (%) (t-1)	78	6		
3	Water Saturation (%) (t-1)	78	Dynamic Attributes		
4	Permeability I(t-1)	72	1	Water Saturation (%) (t-1)(1P)	100
15	Oil Rate (t)	1	2	Oil Saturation (%) (t-1)(1P)	100
16	Gas Rate (t)	1	3	Distance(t)(1I)	92
6			12	Permeability I(t-1)(2P)	42
TOTAL ATTRIBUTES			15	Permeability I(t-1)(2I)	39
21			5		

Reservoir Pressure

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
Dynamic Attributes			4	Top (ft)(1I)	85
1	Reservoir Pressure (psi)(t-1)	100	5	Top (ft)(2P)	79
2	FBH Pressure (psi)(t)	78	6	Pay thickness (ft)(1I)	79
3	FBH Pressure (psi)(t-1)	52	6		
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
TOTAL ATTRIBUTES			3		
17					

Water Saturation

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
Dynamic Attributes			4		
1	Oil Saturation (%) (t-1)	100	Dynamic Attributes		
2	Water Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1)(1P)	100
4	Reservoir Pressure (psi)(t)	23	2	Oil Saturation (%) (t-1)(1P)	100
5	Water Rate (t)	18	2		
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES					
15					

Figure 4-15: Scenario 1 – TDM Input Attributes

The finalized spatio-temporal database was partitioned into training, calibration, and validation datasets. The number of records pertaining to each partition dataset is represented in Figure 4-16.

Figure 4-16: Scenario 1 - Neural Network Data Partitioning

The quality of the estimated results from each trained model is graphically and numerically presented in Figure 4-17. The linearity of the cross plots along with a high R^2 confirms the quality of the trained network.

Scenario 1 – Cross Plots and R^2 Results

Figure 4-17: Scenario 1 – Partitioning Cross Plot Results

4.4.1.2 Scenario 2 – Mixed Partitioning (1 Year Validation)

Mixed partitioning was the method used in the development of the second TDM model. This suggests that once the model is validated, it has a higher degree of confidence associated with the top-down model forecast [17]. Nevertheless, the purpose of the model was solely to perform blind history-matching in time.

Comprehensive Data-Driven Dataset Generation:

The recreation of five predictive data-driven datasets included candidate attributes from the focal well and offset wells (2 offset producers and 2 offset injectors). The development dataset included time ranges from January 1st of 1995 to January 1st of 2017, suggesting forecast in time was not performed. Once attribute selection was performed and development and deployment time ranges were established, data-driven datasets were generated, cleansed based on oil at time “t” and sorted in a chronological order.

Figure 4-18: Scenario 2 - Development Dataset

Data-Driven Model Development:

All the generated data-driven datasets were further compiled by selecting the most influential attributes from KPI analysis (Refer to APPENDIX B: Key Performance Indicators). A list of the final input attributes used in the neural network development is shown in Figure 4-19.

Scenario 2 – TDM Input Attributes

Oil Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			5	TVD (ft)(1I)	73
			6	Top (ft)(2P)	65
			9	TVD (ft)(1P)	55
			11	Pay thickness (ft)(1P)	50
			7		
			Dynamic Attributes		
1	Oil Rate (t-1)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Gas Rate (t-1)	100	3	FBH Pressure (psi)(t-1)(1I)	96
3	Permeability I(t-1)	49	4	Reservoir Pressure (psi)(t-1)(1I)	96
4	Time	48	5	Distance(t)(2P)	96
4			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			12	Distance (t)(1P)	61
			34	Distance(t)(1I)	28
			11		
TOTAL ATTRIBUTES		24			

Gas Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			4	X/Longitude(1I)	84
			5	TVD (ft)(1I)	73
			8	Y/Latitude(1I)	56
			6		
			Dynamic Attributes		
1	Oil Rate (t)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Oil Rate (t-1)	60	2	Distance(t-1)(2P)	97
3	Gas Rate (t-1)	60	3	FBH Pressure (psi)(t-1)(1I)	96
4	Permeability I(t-1)	29	4	Reservoir Pressure (psi)(t-1)(1I)	96
4			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		
TOTAL ATTRIBUTES		22			

Water Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
2	X/Longitude	89	1	X/Longitude(2P)	100
3	Top (ft)	84	2	Top (ft)(2P)	90
9	Porosity (%)	1	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
			5	X/Longitude(2I)	75
			7	TVD (ft)(2I)	65
			6		
			Dynamic Attributes		
1	q(t-1)-Water	100	1	Water Saturation (%) (t-1)(1P)	100
2	Oil Saturation (%) (t-1)	78	2	Oil Saturation (%) (t-1)(1P)	100
3	Water Saturation (%) (t-1)	78	3	Distance(t)(1I)	92
4	Permeability I(t-1)	72	12	Permeability I(t-1)(2P)	42
15	Oil Rate (t)	1	15	Permeability I(t-1)(2I)	39
16	Gas Rate (t)	1	5		
6					
TOTAL ATTRIBUTES		20			

Reservoir Pressure

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
			4	Top (ft)(1I)	85
			5	Top (ft)(2P)	79
			6	Pay thickness (ft)(1I)	79
			6		
			Dynamic Attributes		
1	Reservoir Pressure (psi)(t-1)	100	1	Reservoir Pressure (psi)(t-1)(1P)	100
2	FBH Pressure (psi)(t)	78	2	FBH Pressure (psi)(t-1)(1P)	91
3	FBH Pressure (psi)(t-1)	52	3	FBH Pressure (psi)(t)(1P)	90
12	Water Rate (t)	5	3		
13	Oil Rate (t)	4			
14	Gas Rate (t)	4			
6					
TOTAL ATTRIBUTES		17			

Water Saturation

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
			4		
			Dynamic Attributes		
1	Oil Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1)(1P)	100
2	Water Saturation (%) (t-1)	100	2	Oil Saturation (%) (t-1)(1P)	100
4	Reservoir Pressure (psi)(t)	23	2		
5	Water Rate (t)	18			
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES		15			

Figure 4-19: Scenario 1 – TDM Input Attributes

Each compiled dataset, also referred to as the spatio-temporal database, was partitioned into training, calibration and validation datasets. While the training and calibration datasets were completely randomized, the validation dataset comprised records pertaining to the last year of the dataset (January 1st, 2016 – January 1st, 2017). The number of records pertaining to each partition dataset is represented in Figure 4-20.

Figure 4-20: Scenario 2 – Neural Network Data Partitioning

Estimated results from each data-driven model are graphically and numerically presented in Figure 4-21. Overall, the training, calibration, and validation datasets display satisfactory results. However, the oil model had a lower R^2 value for the calibration and validation datasets.

Scenario 2 – Cross Plots and R^2 Results

Figure 4-21: Scenario 2 – Partitioning Cross Plot Results

4.4.1.3 Scenario 3 – Mixed Partitioning (2 Year Validation)

The third scenario used a similar approach to the second scenario. However, the number of records used in the training and calibration process was decreased while the number of records in the validation dataset was increased. This approach was taken to evaluate the TDM performance on the blind validation dataset with fewer data records in the training dataset.

Comprehensive Data-Driven Dataset Generation:

The development and deployment dataset comprised of time ranges from January 1st of 1995 to January 1st of 2017, suggesting that no forecasting was performed.

Figure 4-22: Scenario 3 – Development Dataset

Data-Driven Model Development:

The data-driven datasets were further compiled by selecting the most influential attributes from KPI analysis (Refer to APPENDIX B: Key Performance Indicators). The list of attributes used as inputs to the neural network is shown in Figure 4-23.

Scenario 3 – TDM Input Attributes

Oil Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
5	TVD(ft)	73	3	Top (ft)(1I)	90
3			5	TVD (ft)(1I)	73
Dynamic Attributes			Dynamic Attributes		
1	Oil Rate (t-1)	100	6	Top (ft)(2P)	65
2	Gas Rate (t-1)	100	9	TVD (ft)(1P)	55
3	Permeability I(t-1)	49	10	X/Longitude(1P)	52
4	Time	48	11	Pay thickness (ft)(1P)	50
4			8		
TOTAL ATTRIBUTES			Dynamic Attributes		
25			1	FBH Pressure (psi)(t)(1I)	100
			2	Distance(t-1)(2P)	97
			3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Gas Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
Dynamic Attributes			4	X/Longitude(1I)	84
1	Oil Rate (t)	100	5	TVD (ft)(1I)	73
2	Oil Rate (t-1)	60	5		
3	Gas Rate (t-1)	60	Dynamic Attributes		
4	Permeability I(t-1)	29	1	FBH Pressure (psi)(t)(1I)	100
4			2	Distance(t-1)(2P)	97
TOTAL ATTRIBUTES			3	FBH Pressure (psi)(t-1)(1I)	96
21			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Water Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
Dynamic Attributes			5	X/Longitude(2I)	75
1	q(t-1)-Water	100	7	TVD (ft)(2I)	65
2	Oil Saturation (%) (t-1)	78	6		
3	Water Saturation (%) (t-1)	78	Dynamic Attributes		
4	Permeability I(t-1)	72	1	Water Saturation (%) (t-1)(1P)	100
15	Oil Rate (t)	1	2	Oil Saturation (%) (t-1)(1P)	100
16	Gas Rate (t)	1	3	Distance(t)(1I)	92
6			12	Permeability I(t-1)(2P)	42
TOTAL ATTRIBUTES			15	Permeability I(t-1)(2I)	39
20			5		

Reservoir Pressure

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
Dynamic Attributes			4	Top (ft)(1I)	85
1	Reservoir Pressure (psi)(t-1)	100	5	Top (ft)(2P)	79
2	FBH Pressure (psi)(t)	78	6	Pay thickness (ft)(1I)	79
3	FBH Pressure (psi)(t-1)	52	6		
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
TOTAL ATTRIBUTES			3		
17					

Water Saturation

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
Dynamic Attributes			4		
1	Oil Saturation (%) (t-1)	100	Dynamic Attributes		
2	Water Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1)(1P)	100
4	Reservoir Pressure (psi)(t)	23	2	Oil Saturation (%) (t-1)(1P)	100
5	Water Rate (t)	18	2		
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES					
15					

Figure 4-23: Scenario 3 – TDM Input Attributes

The training and calibration datasets were randomly assigned. The validation dataset consisted of data records pertaining to the last 2 years of the development dataset (January 1st, 2015 – January 1st, 2017). See Figure 4-24.

Figure 4-24: Scenario 3 – Neural Network Data Partitioning

Cross plots and R^2 values served as a graphical and numerical measurement to determine the quality of the trained data-driven models. Figure 4-25 suggests that the overall performance for the training, calibration, and validation datasets was satisfactory. However, the oil model presented data records spread over the validation cross plot as well as lower R^2 values for both the calibration and validation datasets.

Scenario 3 – Cross Plots and R^2 Results

Figure 4-25: Scenario 3 – Partitioning Cross Plot Results

4.4.1.4 Scenario 4 – Mixed Partitioning (1 Year Forecast)

The fourth scenario was developed with efforts to history match and forecast production, reservoir pressure and water saturation distributions. Once the model was graphically and numerically validated, the TDM was deployed on a blind dataset that was not included in the spatio-temporal database.

Comprehensive Data-Driven Dataset Generation:

Candidate attributes were selected at appropriate timesteps to recreate comprehensive data-driven datasets for each predictive model.

The development dataset consisted of time ranges from January 1st of 1995 until December 31st of 2015. On the other hand, the deployment dataset consisted of time ranges from January 1st of 1995 until January 1st of 2017, suggesting that the TDM model forecasted production, reservoir pressure and water saturation distributions under a variety of operating conditions (i.e. water injection rates, days of production, and flowing bottom-hole pressure). Figure 4-26 illustrates the time ranges for both the development and deployment datasets.

Figure 4-26: Scenario 4: Development and Deployment Datasets

Data-Driven Model Development:

The comprehensive datasets were compiled by reducing the number of potential input attributes to be used in the final spatio-temporal database. KPI analysis provided some insight regarding the most influential attributes with respect to the output attribute (Refer to APPENDIX B: Key Performance Indicators). A larger number of inputs were included in the development of each

predictive model in order to provide more information to the neural network. A list of the input attributes is provided below:

Scenario 4 – TDM Input Attributes

Oil Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(11)	91
2	Porosity (%)	90	3	Top (ft)(11)	90
5	TVD(ft)	73	4	X/Longitude(11)	84
3			5	TVD (ft)(11)	73
Dynamic Attributes			6	Top (ft)(2P)	65
1	Oil Rate (t-1)	100	7	Y/Latitude(1P)	59
2	Gas Rate (t-1)	100	8	Y/Latitude(11)	50
3	Permeability I(t-1)	49	9	TVD (ft)(1P)	55
4	Time	48	10	X/Longitude(1P)	52
9	Completion (ft)(t)	12	11	Pay thickness (ft)(1P)	50
10	Completion (ft)(t-1)	10	16	TVD (ft)(2P)	36
6			20	Y/Latitude(21)	30
TOTAL ATTRIBUTES			30	Pay thickness (ft)(2P)	12
			38	X/Longitude(21)	4
			14		
Dynamic Attributes			Dynamic Attributes		
1	FBH Pressure (psi)(t)(11)	100	1	FBH Pressure (psi)(t)(11)	100
2	Distance(t-1)(2P)	97	2	Distance(t-1)(2P)	97
3	FBH Pressure (psi)(t-1)(11)	96	3	FBH Pressure (psi)(t-1)(11)	96
4	Reservoir Pressure (psi)(t-1)(11)	96	4	Reservoir Pressure (psi)(t-1)(11)	96
5	Distance(t)(2P)	96	5	Distance(t)(2P)	96
6	FBH Pressure (psi)(t)(21)	93	6	FBH Pressure (psi)(t)(21)	93
7	FBH Pressure (psi)(t-1)(21)	92	7	FBH Pressure (psi)(t-1)(21)	92
8	Reservoir Pressure (psi)(t-1)(21)	92	8	Reservoir Pressure (psi)(t-1)(21)	92
9	Water Saturation (%) (t-1)(21)	87	9	Water Saturation (%) (t-1)(21)	87
10	Oil Saturation (%) (t-1)(21)	87	10	Oil Saturation (%) (t-1)(21)	87
39	Completion (ft)(t)(1P)	14	39	Completion (ft)(t)(1P)	14
40	Completion (ft)(t-1)(1P)	13	40	Completion (ft)(t-1)(1P)	13
			10		

Gas Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(11)	91
2			3	Top (ft)(11)	90
Dynamic Attributes			4	X/Longitude(11)	84
1	Oil Rate (t)	100	5	TVD (ft)(11)	73
2	Oil Rate (t-1)	60	8	Y/Latitude(11)	56
3	Gas Rate (t-1)	60	6		
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(11)	100
TOTAL ATTRIBUTES		22	2	Distance(t-1)(2P)	97
			3	FBH Pressure (psi)(t-1)(11)	96
			4	Reservoir Pressure (psi)(t-1)(11)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(21)	93
			7	FBH Pressure (psi)(t-1)(21)	92
			8	Reservoir Pressure (psi)(t-1)(21)	92
			9	Water Saturation (%) (t-1)(21)	87
			10	Oil Saturation (%) (t-1)(21)	87
			10		

Water Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(21)	79
Dynamic Attributes			5	X/Longitude(21)	75
1	q(t-1)-Water	100	7	TVD (ft)(21)	65
2	Oil Saturation (%) (t-1)	78	6		
3	Water Saturation (%) (t-1)	78	Dynamic Attributes		
4	Permeability I(t-1)	72	1	Water Saturation (%) (t-1)(1P)	100
15	Oil Rate (t)	1	2	Oil Saturation (%) (t-1)(1P)	100
16	Gas Rate (t)	1	3	Distance(t)(11)	92
6			12	Permeability I(t-1)(2P)	42
TOTAL ATTRIBUTES			15	Permeability I(t-1)(21)	39
			5		

Reservoir Pressure

FOCAL WELL			OFFSET WELLS			
Static Attributes			Static Attributes			
Rank	Attribute	DOI	Rank	Attribute	DOI	
	0		12	Porh(1-sw)(11)	58	
Dynamic Attributes			15	Pay thickness (ft)(21)	45	
1	Reservoir Pressure (psi)(t-1)	100	21	Permeability (md)(11)	25	
2	FBH Pressure (psi)(t)	78	23	Pay thickness (ft)(2P)	24	
4	Oil Saturation (%) (t-1)	40	31	Pay thickness (ft)(1P)	15	
5	Water Saturation (%) (t-1)	40		5		
7	Permeability I(t-1)	18	Dynamic Attributes			
12	Oil Rate (t-1)	5	1	Reservoir Pressure (psi)(t-1)(1P)	100	
13	Oil Rate (t)	4	3	FBH Pressure (psi)(t)(1P)	90	
14	Gas Rate (t)	4	6	Reservoir Pressure (psi)(t-1)(2P)	50	
17	Oil Rate (t-1)	3	7	FBH Pressure (psi)(t)(2P)	45	
	9		9	Distance(t)(21)	34	
TOTAL ATTRIBUTES			33	11	Distance(t)(11)	31
				13	Water Saturation (%) (t-1)(2P)	24
				14	Oil Saturation (%) (t-1)(2P)	24
				19	FBH Pressure (psi)(t)(21)	16
				21	Reservoir Pressure (psi)(t-1)(21)	16
				24	Permeability I(t-1)(21)	14
				26	Water Injection Rate(t)(11)	11
				31	Distance(t)(1P)	10
				39	Reservoir Pressure (psi)(t-1)(11)	8
				40	FBH Pressure (psi)(t)(11)	7
				44	Completion (ft)(1P)	6
				46	Distance(t)(2P)	6
				51	Water Saturation (%) (t-1)(21)	5
				52	Oil Saturation (%) (t-1)(21)	5
				19		

Water Saturation

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
3	Y/Latitude	65	36	Permeability (md)(11)	4
5	Porh(1-sw)	26	1		
7	Porosity (%)	22	Dynamic Attributes		
2			5	Distance(t)(11)	50
Dynamic Attributes			9	Distance(t)(21)	46
1	Oil Saturation (%) (t-1)	100	28	Water Saturation (%) (t-1)(11)	20
2	Water Saturation (%) (t-1)	100	29	Oil Saturation (%) (t-1)(11)	20
4	Reservoir Pressure (psi)(t)	23	30	Distance(t)(1P)	19
5	Water Rate (t)	18	32	Water Saturation (%) (t-1)(21)	18
10	Oil Rate (t)	8	33	Oil Saturation (%) (t-1)(21)	18
11	Gas Rate (t)	8	35	Distance(t)(2P)	17
6			36	Permeability I(t-1)(1P)	16
TOTAL ATTRIBUTES			43	Permeability I(t-1)(2P)	14
			48	Permeability I(t-1)(11)	8
			11		

Figure 4-27: Scenario 4 – TDM Input Attributes

Each spatio-temporal database was partitioned into the training, calibration, and validation datasets. The training and calibration dataset records were randomly assigned while the validation dataset included data records pertaining to the last year of the development dataset (January 1st, 2015 – December 31st, 2015). The number of records pertaining to each partition dataset is represented in Figure 4-28.

Figure 4-28: Scenario 4 – Neural Network Data Partitioning

Graphical and numerical correlations between the data-driven models' estimated values and the actual data are displayed in Figure 4-29. The figure shows that the lowest calibration and validation R^2 values pertain to the oil model. Acceptable R^2 values and linearity from the cross plots confirm a good quality trained network [25].

Scenario 4 – Cross Plots and R^2 Results

Figure 4-29: Scenario 4 – Partitioning Cross Plot Results

4.4.1.5 Scenario 5 – Mixed Partitioning (2 Year Forecast)

The fifth scenario followed a similar approach to scenario 4. However, the forecasting time range was increased from 1 year to 2 years.

Comprehensive Data-Driven Dataset Generation:

Candidate attributes for the focal and offset wells (2 offset producers and 2 offset injectors) were selected at appropriate timesteps of “t” and “t-1”. Furthermore, the development dataset was composed of records from January 1st of 1995 until December 31st of 2014 while the deployment dataset ranged from January 1st of 1995 to January 1st of 2017.

Figure 4-30: Scenario 5 – Development and Deployment Datasets

Data-Driven Model Development:

Neural network input attributes, displayed in Figure 4-31, were selected according to the KPI analysis performed (Refer to APPENDIX B: Key Performance Indicators).

Scenario 5 – TDM Input Attributes

Oil Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(1I)	91
2	Porosity (%)	90	3	Top (ft)(1I)	90
5	TVD(ft)	73	5	TVD (ft)(1I)	73
3			6	Top (ft)(2P)	65
Dynamic Attributes			9	TVD (ft)(1P)	55
1	Oil Rate (t-1)	100	10	X/Longitude(1P)	52
2	Gas Rate (t-1)	100	11	Pay thickness (ft)(1P)	50
3	Permeability I(t-1)	49	7		
4	Time	48	Dynamic Attributes		
9	Completion (ft)(t)	12	1	FBH Pressure (psi)(t)(1I)	100
5			2	Distance(t-1)(2P)	97
TOTAL ATTRIBUTES			3	FBH Pressure (psi)(t-1)(1I)	96
25			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Gas Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
Dynamic Attributes			4	X/Longitude(1I)	84
1	Oil Rate (t)	100	5	TVD (ft)(1I)	73
2	Oil Rate (t-1)	60	8	Y/Latitude(1I)	56
3	Gas Rate (t-1)	60	6		
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
TOTAL ATTRIBUTES			2	Distance(t-1)(2P)	97
22			3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Water Rate

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
Dynamic Attributes			5	X/Longitude(2I)	75
1	q(t-1)-Water	100	7	TVD (ft)(2I)	65
2	Oil Saturation (%) (t-1)	78	6		
3	Water Saturation (%) (t-1)	78	Dynamic Attributes		
4	Permeability I(t-1)	72	1	Water Saturation (%) (t-1)(1P)	100
15	Oil Rate (t-1)	1	2	Oil Saturation (%) (t-1)(1P)	100
16	Gas Rate (t-1)	1	3	Distance(t)(1I)	92
6			12	Permeability I(t-1)(2P)	42
TOTAL ATTRIBUTES			15	Permeability I(t-1)(2I)	39
20			5		

Reservoir Pressure

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
Dynamic Attributes			4	Top (ft)(1I)	85
1	Reservoir Pressure (psi)(t-1)	100	5	Top (ft)(2P)	79
2	FBH Pressure (psi)(t)	78	6	Pay thickness (ft)(1I)	79
3	FBH Pressure (psi)(t-1)	52	6		
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
TOTAL ATTRIBUTES			3		
17					

Water Saturation

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
Dynamic Attributes			4		
1	Oil Saturation (%) (t-1)	100	Dynamic Attributes		
2	Water Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1)(1P)	100
4	Reservoir Pressure (psi)(t)	23	2	Oil Saturation (%) (t-1)(1P)	100
5	Water Rate (t)	18	2		
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES					
15					

Figure 4-31: Scenario 5 – TDM Input Attributes

The spatio-temporal database was partitioned into three different datasets. The training and calibration datasets were randomly assigned while the validation dataset consisted of records pertaining to the last year of the dataset (January 1st, 2014 – December 31st, 2014).

Figure 4-32: Scenario 5 – Neural Network Data Partitioning

Scenario 4 – Cross Plots and R^2 Results

Figure 4-33: Scenario 5 – Partitioning Cross Plot Results

4.4.2 Summary of Conducted Scenarios

The number of records used in the training, calibration, and validation datasets for all five TDM models is shown in Table 4-2.

Table 4-2: Partitioning No. of Records

Scenario No.	TDM Model Name	TDM Partitioning Records				
		Training	Calibration	Validation	Forecast	Total
Scenario 1	RP TDM	4,681	585	585	-	5,851
Scenario 2	MP TDM 1V	4,431	1,108	312	-	5,851
Scenario 3	MP TDM 2V	4,154	1,039	658	-	5,851
Scenario 4	MP TDM 1V 1B	4,154	1,039	346	312	5,539
Scenario 5	MP TDM 1V 2B	3,871	968	354	658	5,193

Moreover, the number of epochs that the neural network was exposed to during the training process and the number of input attributes used in the development of the neural network are summarized in Table 4-3.

Table 4-3: Predictive Model Input Attributes and No. of Epochs Summary

	Predictive Model	TDM Models				
		Scenario 1 RP TDM	Scenario 2 MP TDM 1V	Scenario 3 MP TDM 2V	Scenario 4 MP TDM 1V 1F	Scenario 5 MP TDM 1V 2F
No. Inputs	Oil (77)	25	24	25	35	25
	Gas (77)	22	22	21	22	22
	Water (79)	21	20	20	21	20
	Res Press. (83)	17	17	17	33	17
	Water Sat (86)	15	15	15	20	15
No. Epochs	Oil	18,297	30,905	33,256	18,637	18,609
	Gas	15,949	33,052	33,113	32,068	32,628
	Water	10,636	37,938	22,443	18,814	19,501
	Res Press.	27,379	43,524	35,646	12,829	18,882
	Water Sat	9,985	31,138	13,206	15,013	15,168

The performance of each predictive model was evaluated graphically and numerically through different criteria, including cross plots and different evaluation metrics summarized in Table 4-4 and Table 4-5.

Table 4-4: TDM Model R.Squared Results

Partition	Predictive Data-Driven Model	TDM Models				
		Scenario 1 RP TDM	Scenario 2 MP TDM 1V	Scenario 3 MP TDM 2V	Scenario 4 MP TDM 1V 1F	Scenario 5 MP TDM 1V 2F
Training	Oil Rate	93.90%	95.36%	95.90%	95.50%	93.77%
	Gas Rate	98.23%	99.04%	99.02%	99.18%	98.62%
	Water Rate	96.19%	97.52%	97.24%	97.04%	96.64%
	Reservoir Pressure	99.30%	98.89%	98.85%	99.32%	98.63%
	Water Saturation	99.68%	99.22%	99.59%	99.68%	99.56%
Calibration	Oil Rate	86.16%	79.03%	80.02%	91.38%	89.78%
	Gas Rate	97.15%	98.38%	98.56%	97.26%	98.05%
	Water Rate	95.46%	96.79%	95.94%	95.39%	95.33%
	Reservoir Pressure	97.33%	98.74%	98.64%	98.11%	98.03%
	Water Saturation	98.92%	99.42%	99.62%	98.92%	99.60%
Validation	Oil Rate	91.00%	80.66%	75.72%	86.09%	80.31%
	Gas Rate	97.92%	94.74%	94.40%	94.97%	94.69%
	Water Rate	92.92%	91.33%	91.81%	96.98%	97.01%
	Reservoir Pressure	97.98%	98.67%	98.59%	98.61%	98.56%
	Water Saturation	99.81%	99.36%	99.60%	99.81%	99.78%
All Cases	Oil Rate	93.10%	91.18%	91.97%	94.61%	92.71%
	Gas Rate	98.10%	98.87%	98.81%	98.86%	98.45%
	Water Rate	95.77%	96.99%	96.31%	96.81%	96.45%
	Reservoir Pressure	98.83%	98.85%	98.79%	99.06%	98.53%
	Water Saturation	99.56%	99.26%	99.61%	99.56%	99.59%

Table 4-5: TDM Model MAE Results

Partition	Predictive Data-Driven Model	TDM Models				
		Scenario 1 RP TDM	Scenario 2 MP TDM 1V	Scenario 3 MP TDM 2V	Scenario 4 MP TDM 1V 1F	Scenario 5 MP TDM 1V 2F
Training	Oil Rate	198.84	169.13	167.65	160.99	204.87
	Gas Rate	50,510.60	37,996.02	38,185.97	36,443.51	45,092.99
	Water Rate	98.49	72.09	82.90	81.76	86.51
	Reservoir Pressure	23.74	20.64	20.90	19.74	23.71
	Water Saturation	0.54	0.84	0.50	0.45	0.50
Calibration	Oil Rate	217.99	210.84	199.90	190.77	238.87
	Gas Rate	55,661.31	39,483.52	44,222.94	39,919.65	50,828.20
	Water Rate	97.31	71.61	80.87	85.98	95.36
	Reservoir Pressure	24.58	23.28	22.64	26.64	29.33
	Water Saturation	0.54	0.81	0.50	0.58	0.50
Validation	Oil Rate	202.26	191.61	201.33	161.98	191.73
	Gas Rate	52,756.45	46,679.03	46,865.99	43,517.47	48,850.92
	Water Rate	116.98	174.22	189.33	119.58	136.30
	Reservoir Pressure	23.01	23.29	25.06	27.45	24.75
	Water Saturation	0.55	0.87	0.69	0.49	0.53
All Cases	Oil Rate	201.10	178.22	177.16	166.64	210.31
	Gas Rate	51,250.13	38,740.72	40,234.14	37,537.44	46,213.72
	Water Rate	100.22	77.45	94.51	84.92	91.55
	Reservoir Pressure	23.75	21.28	21.68	21.16	24.83
	Water Saturation	0.54	0.84	0.52	0.48	0.50

CHAPTER 5

5 RESULTS AND DISCUSSION

A total of five different TDM models were built from data generated from a numerical reservoir model.

Each TDM was composed of five interconnected predictive models that were trained, calibrated and validated in order to history match oil, gas, and water production, reservoir pressure and water saturation distributions while varying the number of input attributes and partitioning method. The last two TDM models were further deployed on a blind dataset to evaluate their forecast performance.

5.1 Entire Field:

The TDM's entire field performance was evaluated by comparing the cumulative production rates from the TDM model and the actual numerical reservoir model. Table 5-1 suggests that scenarios 1, 4, and 5 overestimated the field's oil, gas, and water cumulative productions as shown in Figure 5-1, Figure 5-4, and Figure 5-5 respectively. The second scenario underestimated the total field's oil production by 0.99% and water production by 1.84%, while the gas production was overestimated by 2.18% as displayed in Figure 5-2. The third scenario overestimated the field's oil and gas total production by 0.90% and 2.37% respectively, while it underestimated the field's water cumulative production by 3.83% as shown in Figure 5-3.

Table 5-1: History Match – Cumulative Field Production Comparison

Numerical Reservoir Model Cumulative Production		TDM Model - Entire Field Cumulative Production				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Oil	6,223,078 bbl	-1.13%	0.99%	-0.90%	-1.29%	-0.52%
Gas	2,597,680,628 scf	-1.74%	-2.18%	-2.37%	-1.84%	-2.03%
Water	3,399,966 bbl	-2.56%	1.84%	3.83%	-0.72%	-0.26%

Table 5-2, on the other hand, provides a cumulative production comparison that takes into account forecasted production from the last two TDM models. The table indicates that the fourth TDM significantly overestimated the forecasted oil, gas, and water productions by 12.76%, 10.57%, and 21.69% respectively (See Figure 5-4). This was primarily attributed to wells 036, 038, 039, 042, 050, 052, 054 and 055 that, despite having an accurate history match, had poor forecast results when compared to the actual data. The production profiles of each of these wells is found in Appendix F: Scenario 4 – Mixed Partitioning TDM (1 Year Forecast) .

The last TDM had a more accurate forecasting performance, although each predictive model was trained for a fewer number of epochs and with a fewer number of input attributes that are summarized in Table 4-3. The field’s cumulative gas and water production were overestimated by 1.52% and 2.05% respectively while the oil was underestimated by 5.32% (See Figure 5-5).

Table 5-2: History Match and Forecast – Cumulative Field Production

Numerical Reservoir Model Cumulative Production		TDM Model - Entire Field Cumulative Production				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Oil	6,223,078 bbl	-1.13%	0.99%	-0.90%	-12.76%	5.32%
Gas	2,597,680,628 scf	-1.74%	-2.18%	-2.37%	-10.57%	-1.52%
Water	3,399,966 bbl	-2.56%	1.84%	3.83%	-21.69%	-2.05%

Entire field production profiles for all TDM models are illustrated below:

Entire Reservoir

Scenario 1 – Random Partitioning TDM

Figure 5-1: Scenario 1 – Entire Field Production Profiles

Entire Reservoir

Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

Figure 5-2: Scenario 2 – Entire Field Production Profiles

Entire Reservoir

Scenario 3 – Mixed Partitioning TDM (2 Year Validation)

Figure 5-3: Scenario 3 – Entire Field Production Profiles

Entire Reservoir

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Figure 5-4: Scenario 4 – Entire Field Production Profiles

Entire Reservoir

Scenario 5 – Mixed Partitioning TDM (2 Year Validation)

Figure 5-5: Scenario 5 – Entire Field Production Profiles

Furthermore, heat maps were generated to visualize reservoir pressure and water saturation distributions at different points in time by interpolating between the values reported at the well locations. Cubic interpolation was the preferred method as it provided the smoothest distribution maps against linear and nearest neighbor interpolations that resulted in distribution discontinuities. Figure 5-7 and Figure 5-8 shows distribution maps at selected timesteps during blind validation and forecast. For example, if the second scenario performed blind history-matching from January 1st of 2016 until January 1st of 2017, the most appropriate timestep to visualize the reservoir pressure and water saturation distributions during the blind validation was in June of 2016.

Figure 5-6: Selected Dates for Distribution Maps During Validation and Forecast

Water saturation distribution maps had higher percentage error near the boundaries of the reservoir. This was potentially influenced by the following:

- a. The difference between the numerical reservoir boundary and the TDM's reservoir boundary. As it was previously described in section 4.3.1, the TDM boundary was manually drawn as closely as possible to the numerical reservoir boundary. This approach resulted in a misleading interpolation near the boundary of the reservoir.
- b. Wells with a shorter production life located near the boundaries of the reservoir had less data to obtain an appropriate trend.

- c. Water saturation values from the neural network were not reported at timesteps when oil production was zero. As a matter of fact, a forward filling technique was used to fill missing values.

Moreover, the percentage error for the 2-year-forecast TDM was lower for both reservoir pressure and water saturation distributions. As it will be discussed in upcoming sections, the 2-year-forecast TDM had a better forecasting performance overall when compared to the 1-year-forecast TDM. This is potentially related to the input attributes used in the development of each predictive model.

Distribution Maps During Validation

Scenario 1 – Random Partitioning TDM

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Scenario 3 – Mixed Partitioning TDM (2 Year Validation)

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Reservoir Pressure (psi) at 2014-06-30

Water Saturation (%) at 2014-06-30

Figure 5-7: Distribution Maps During Validation

Distribution Maps During Forecast

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Figure 5-8: Distribution Maps During Forecast

5.2 Well by Well:

Although high R^2 and low MSE described the quality of the trained networks, these criteria were re-evaluated by visually inspecting the history match of production profiles both individually and collectively.

5.2.1 Individual Production Analysis:

Oil, gas, and water production rates were evaluated on an individual well by well basis and labeled as having a “good”, “average” or “poor” match against the actual production rates. Wells with a good match had a close if not an exact match against the actual production rate being evaluated. Figure 5-9 displays examples of individual production profiles with a good history match. Wells with an average prediction were able to match production for some portions of time while at other instances, the predictions did not match the simulation data as closely. Examples of average predictions are displayed in Figure 5-10. Wells with a poor match had been unable to closely follow the actual production trend. Examples of poor predictions are displayed in Figure 5-11.

Good History Match of Individual Production Rates

Figure 5-9: Good History Match of Individual Production Profiles

Average History Match of Individual Production Rates

Figure 5-10: Average History Match of Individual Production Profiles

Poor History Match of Individual Production Rates

Figure 5-11: Poor History Match of Individual Production Profiles

Table 5-3 provides the number or percentage of wells with good, average, and poor history match of three production rates for every TDM model. Overall, more than 70% of the wells presented good history matches for every production rate.

The fourth TDM model had the highest percentage of wells with a good history match of oil production while the second TDM had the highest number of wells with good water predictions. The gas rate, on the other hand, remained highly accurate across all the TDM models. Moreover, the number of wells with poor history matches did not exceed 2%.

Table 5-3: History Match Accuracy of Individual Production Rates

History Match Accuracy		Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
		No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage
Oil	Good	42	74%	40	70%	42	74%	51	89%	40	70%
	Average	14	25%	17	30%	15	26%	6	11%	17	30%
	Poor	1	2%	0	0%	0	0%	0	0%	0	0%
Gas	Good	57	100%	57	100%	57	100%	57	100%	57	100%
	Average	0	0%	0	0%	0	0%	0	0%	0	0%
	Poor	0	0%	0	0%	0	0%	0	0%	0	0%
Water	Good	46	81%	52	91%	47	82%	50	88%	50	88%
	Average	11	19%	4	7%	9	16%	5	9%	6	11%
	Poor	0	0%	1	2%	1	2%	2	4%	1	2%

In a similar fashion, Table 5-4 provides the number or percentage of wells with good, average, and poor forecast of three production rates for the TDM models that were deployed on a blind dataset. The fourth TDM had a total of 35 wells with production from January 1st, 2016 until January 1st, 2017 (1-year forecast) while the fifth scenario had a total of 38 wells with production from January 1st, 2015 until January 1st, 2017 (2-year-forecast). The table suggests that the fifth TDM (2-year-forecast) had a higher number of wells with good forecast production rates. The fifth TDM also had a lower number of wells with poor forecast performance.

Table 5-4: Forecast of Individual Production Rates

Forecast Production Accuracy		Scenario 4		Scenario 5	
		No. Wells	Percentage	No. Wells	Percentage
Oil	Good	15	44%	21	57%
	Average	6	18%	14	38%
	Poor	13	38%	2	5%
Gas	Good	24	71%	32	86%
	Average	1	3%	5	14%
	Poor	9	26%	0	0%
Water	Good	20	59%	27	73%
	Average	4	12%	10	27%
	Poor	10	29%	0	0%

5.2.2 Collective Production Analysis:

Production rates were collectively evaluated and labeled as having an “good”, “average”, or “poor” history match of production. Example of wells with a good, average, and poor predictions are shown in Figure 5-12, Figure 5-13, and Figure 5-14 respectively. Furthermore, the last two TDM models were evaluated based on their forecast predictions. Figure 5-15, Figure 5-16, and Figure 5-17, illustrate wells with good, average, and poor forecast production.

Acceptable History Match of Production

Scenario 1 – Random Partitioning

Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

Scenario 3 – Mixed Partitioning TDM (2 Year Validation)

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Figure 5-12: Acceptable History Match of Production

Average History Match of Production

Scenario 1 – Random Partitioning TDM

Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

Scenario 3 – Mixed Partitioning TDM (2 Year Validation)

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Figure 5-13: Average History Match of Production

Poor History Match of Production

Scenario 1 – Random Partitioning TDM

Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

Scenario 3 – Mixed Partitioning TDM (2 Year Validation)

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Figure 5-14: Poor Production History Match

Good Forecast Production

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Well-019

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Well-010

Figure 5-15: Good Forecast Production

Average Production Forecast

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Figure 5-16: Average Forecast Production

Poor Production Forecast

Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

Scenario 5 – Mixed Partitioning TDM (2 Year Forecast)

Figure 5-17: Poor Production Forecast

Production rates for every well were collectively evaluated. Table 5-5 provides both the number and percentage of wells with good, average, and poor history match for every TDM model.

Table 5-5: History Match Production Accuracy

History Match Accuracy Overall Production	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage	No. Wells	Percentage
Good	28	49%	28	49%	22	39%	40	69%	29	51%
Average	28	49%	27	47%	32	56%	17	29%	27	47%
Poor	1	2%	2	4%	3	5%	0	0%	1	2%

The TDM with 1-year forecast used a higher number of input attributes in the development of each predictive model and was trained for a higher number of epochs. The statistics suggest that 89% of the wells in the field had good history match of oil production, 100% had a good history match of gas production, and 88% had a good history match of water production. After the model was deployed on a blind dataset, 44% of the wells had a good oil production forecast, 71% had a good gas production forecast, and 59% with had a good water production forecast.

The TDM with 2-year-forecast, was trained for a fewer number of epochs and with fewer input attributes. Although the percentage of wells with good history match of production was lower than the TDM with 1-year forecast, Table 5-6 suggests that the overall performance during forecast were more reasonable.

Table 5-6: Production Forecast

Forecast Accuracy Overall Production	Scenario 4		Scenario 5	
	No. Wells	Percentage	No. Wells	Percentage
Good	10	29%	11	30%
Average	11	32%	19	51%
Poor	13	38%	7	19%

CHAPTER 6

6 CONCLUSIONS

Sufficient data was generated from a numerical reservoir simulation model that recreated complexities from real-industry applications. The purpose of this thesis was to implement artificial intelligence and machine learning techniques via Top Down Modeling to history match and forecast oil, gas, and water production, reservoir pressure and water saturation distributions.

The thesis was accomplished by collecting, cleansing, and transforming the generated data into a useful standardized format to proceed with building a total of five TDMs composed of five interconnected predictive models. Each predictive model was trained, calibrated, and validated to ensure the teaching process was a success.

Linearity of cross plots and evaluation metrics, such as high R^2 and low MAE values, were graphical and numerical measurements used as an indication of the quality of the trained networks. Moreover, a visual inspection of the history-matched and forecasted production data vs the simulation data was conducted to once again verify the quality of the developed TDMs.

The different TDM models developed suggest that well-trained networks are capable of history-matching past production data as well as reservoir pressure and water saturation distributions using random and mixed partitioning methods.

The most accurate history-matched results were achieved by the 1-year forecast TDM trained with a higher number of input attributes than the other TDMs. The results indicate that 89% of wells had a good history match of oil production, nearly 100% of wells had a good history match of gas production, and 88% of wells had a good history match of water production. When considering all three plots' quality at once, 66% of the wells had a good history match of production.

The 2-year-forecast TDM resulted in lower percentages of wells with good history matches for oil, gas, and water production rates. Similarly, the number of wells was lower when evaluating the production rates collectively. However, the neural network's prediction during forecast resulted in 53% of accuracy for oil, 86% for gas, and 73% for water. The quality of the forecast when

evaluating the three production rates collectively resulted in 30% of the wells with a good forecast, 51% had an average forecast, and 19% had a poor forecast.

6.1 Future Work

Due to time limitations in the development of different predictive models, the history match and blind history matches were validated while the TDM models with forecast are yet to be improved and validated. The quality of the TDM models is subject to the importance of quantity and quality of data used in the development of a TDM [26].

Moreover, the application of feature selection methods highly impacts the accuracy of predictive models during blind history-matching and forecasting. The TDM models that were deployed on blind datasets can result in a more reliable forecast by investigating efficient sets of input attributes.

Additionally, the error near the boundaries of the water saturation distribution maps was potentially attributed to forward filling unreported values at the well locations at timesteps when there was no oil production. These events can be addressed by implementing interpolation techniques that take into account time and space.

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APPENDIX

7 Appendix A: Well Biography

The following plots provide information regarding the focal well and its offset producers and injectors. The plots include production profiles (oil, gas and water), water cut, bottom-hole pressure behavior, completion footage and the well's location.

The focal well is shown in color red, the offset producers are shown in green and the offset injectors are shown in blue in the map located at the bottom-left of the graph. The plot convention is located at the top-left of the graph.

Figure 7-1: Well-001 Biography

Figure 7-2: Well-002 Biography

Figure 7-3: Well-003 Biography

Figure 7-4: Well-004 Biography

Figure 7-5: Well-005 Biography

Figure 7-6: Well-006 Biography

Figure 7-7: Well-007 Biography

Figure 7-8: Well-008 Biography

Figure 7-9: Well-009 Biography

Figure 7-10: Well-010 Biography

Figure 7-11: Well-011 Biography

Figure 7-12: Well-012 Biography

Figure 7-13: Well-013 Biography

Figure 7-14: Well-014 Biography

Figure 7-15: Well-015 Biography

Figure 7-16: Well-016 Biography

Figure 7-17: Well-017 Biography

Figure 7-18: Well-018 Biography

Figure 7-19: Well-019 Biography

Figure 7-20: Well-020 Biography

Figure 7-21: Well-021 Biography

Figure 7-22: Well-022 Biography

Figure 7-23: Well-023 Biography

Figure 7-24: Well-024 Biography

Figure 7-25: Well-025 Biography

Figure 7-26: Well-026 Biography

Figure 7-27: Well-027 Biography

Figure 7-28: Well-028 Biography

Figure 7-29: Well-029 Biography

Figure 7-30: Well-030 Biography

Figure 7-31: Well-031 Biography

Figure 7-32: Well-032 Biography

Figure 7-33: Well-033 Biography

Figure 7-34: Well-034 Biography

Figure 7-35: Well-035 Biography

Figure 7-36: Well-036 Biography

Figure 7-37: Well-037 Biography

Figure 7-38: Well-038 Biography

Figure 7-39: Well-039 Biography

Figure 7-40: Well-040 Biography

Figure 7-41: Well-041 Biography

Figure 7-42: Well-042 Biography

Figure 7-43: Well-043 Biography

Figure 7-44: Well-044 Biography

Figure 7-45: Well-045 Biography

Figure 7-46: Well-046 Biography

Figure 7-47: Well-047 Biography

Figure 7-48: Well-048 Biography

Figure 7-49: Well-049 Biography

Figure 7-50: Well-050 Biography

Figure 7-51: Well-051 Biography

Figure 7-52: Well-052 Biography

Figure 7-53: Well-053 Biography

Figure 7-54: Well-054 Biography

Figure 7-55: Well-055 Biography

Figure 7-56: Well-056 Biography

Figure 7-57: Well-057 Biography

8 APPENDIX B: Key Performance Indicators

Four different KPI analysis were performed as a guiding tool to identify the most influential input attributes with respect to an output attribute of interest. The first and second KPI targeted the focal well's static and dynamic attributes while the third and fourth KPI targeted the offset wells' static and dynamic attributes respectively.

8.1 Oil Rate

Figure 8-1: Oil Rate – Focal Static Attributes KPI

Figure 8-2: Oil Rate – Focal Dynamic Attributes KPI

Figure 8-3: Oil Rate – Offset Static Attributes KPI

Figure 8-4: Oil Rate – Offset Dynamic Attributes KPI

8.2 Gas Rate

Figure 8-5: Gas Rate – Focal Static Attributes KPI

Figure 8-6: Gas Rate – Focal Dynamic Attributes KPI

Figure 8-7: Gas Rate – Offset Static Attributes KPI

Figure 8-8: Gas Rate – Offset Dynamic Attributes KPI

8.3 Water Rate

Figure 8-9: Water Rate – Focal Static Attributes KPI

Figure 8-10: Water Rate – Focal Dynamic Attributes KPI

Figure 8-11: Water Rate – Offset Static Attributes KPI

Figure 8-12: Water Rate – Offset Dynamic Attributes KPI

8.4 Reservoir Pressure

Figure 8-13: Reservoir Pressure – Focal Static Attributes KPI

Figure 8-14: Reservoir Pressure – Focal Dynamic Attributes KPI

Figure 8-15: Reservoir Pressure – Offset Static Attributes KPI

Figure 8-16: Reservoir Pressure – Offset Dynamic Attributes KPI

8.5 Water Saturation

Figure 8-17: Water Saturation – Focal Static Attributes KPI

Figure 8-18: Water Saturation – Focal Dynamic Attributes KPI

Figure 8-19: Water Saturation – Offset Static Attributes KPI

Figure 8-20: Water Saturation – Focal Dynamic Attributes KPI

9 APPENDIX C: Scenario 1 – Random Partitioning TDM

9.1 Input Attributes

The number of input attributes used in the development of each data-driven model was based on KPI analysis and domain expertise. The following tables provide a list of static and dynamic attributes for both the focal and offset wells. Each table is composed of three columns that indicate the ranking, name of the input attribute, and its degree of influence (DOI) with respect to the output model.

9.1.1 Oil Predictive Model

The oil model consisted of a total of 25 input attributes for the development of the neural network. 8 attributes provided static and dynamic information regarding the focal well while 17 attributes provided static and dynamic information from the offset wells.

Flowing bottom-hole pressure and reservoir pressure from 2 offset injectors have a high degree of influence (DOI) on oil production. Similarly, static attributes from the first injector influenced the oil production.

Oil Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(1I)	91
2	Porosity (%)	90	3	Top (ft)(1I)	90
3	TVD (ft)	52	5	TVD (ft)(1I)	73
8	Pay Thickness (ft)	23	6	Top (ft)(2P)	65
4			9	TVD (ft)(1P)	55
			10	X/Longitude(1P)	52
			11	Pay thickness (ft)(1P)	50
			7		
Dynamic Attributes			Dynamic Attributes		
1	Oil Rate (t-1)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Gas Rate (t-1)	100	2	Distance(t-1)(2P)	97
3	Permeability I(t-1)	49	3	FBH Pressure (psi)(t-1)(1I)	96
4	Time	48	4	Reservoir Pressure (psi)(t-1)(1I)	96
4			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		
TOTAL ATTRIBUTES		25			

Figure 9-1: Scenario 1 - Oil Model Input Attributes

9.1.2 Gas Predictive Model

The gas model consisted of 22 total input attributes. Higher DOI was attributed to offset injector dynamic properties. Moreover, static attributes from the first injector had higher influence on gas production.

Gas Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
Dynamic Attributes			4	X/Longitude(1I)	84
1	Oil Rate (t)	100	5	TVD (ft)(1I)	73
2	Oil Rate (t-1)	60	8	Y/Latitude(1I)	56
3	Gas Rate (t-1)	60	6		
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
TOTAL ATTRIBUTES			2	Distance(t-1)(2P)	97
		22	3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Figure 9-2: Scenario 1 - Gas Model Input Attributes

9.1.3 Water Predictive Model

The water model consisted of 22 total input attributes. Dynamic saturations from the closest producer had a higher DOI on water production. Furthermore, top and TVD from the second closest producer and injector seemed to contribute more towards water production.

Water Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
2	X/Longitude	89	1	X/Longitude(2P)	100
3	Top (ft)	84	2	Top (ft)(2P)	90
9	Porosity (%)	1	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
			5	X/Longitude(2I)	75
			7	TVD (ft)(2I)	65
			6		
Dynamic Attributes			Dynamic Attributes		
1	Water Rate (t-1)	100	1	Water Saturation (t-1)(1P)	100
2	Oil Saturation (t-1)	78	2	Oil Saturation (t-1)(1P)	100
3	Water Saturation (t-1)	78	3	Distance(t)(1I)	92
4	Permeability I(t-1)	72	12	Permeability I(t-1)(2P)	42
15	Oil Rate (t)	1	15	Permeability I(t-1)(2I)	39
16	Gas Rate (t)	1	5		
6					
TOTAL ATTRIBUTES		21			

Figure 9-3: Scenario 1 - Water Model Input Attributes

9.1.4 Reservoir Pressure Predictive Model

The water model consisted of a total of 17 input attributes. Offset positioning from the offset wells, flowing bottom-hole pressure and reservoir pressure from the closest producer had higher DOI on reservoir pressure.

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
			4	Top (ft)(1I)	85
			5	Top (ft)(2P)	79
			6	Pay thickness (ft)(1I)	79
			6		
Dynamic Attributes			Dynamic Attributes		
1	Reservoir Pressure (psi)(t-1)	100	1	Reservoir Pressure (psi)(t-1)(1P)	100
2	FBH Pressure (psi)(t)	78	2	FBH Pressure (psi)(t-1)(1P)	91
3	FBH Pressure (psi)(t-1)	52	3	FBH Pressure (psi)(t)(1P)	90
12	Water Rate (t)	5	3		
13	Oil Rate (t)	4			
14	Gas Rate (t)	4			
6					
TOTAL ATTRIBUTES		17			

Figure 9-4: Scenario 1 – Reservoir Pressure Model Input Attributes

9.1.5 Water Saturation Predictive Model

The water model consisted of a total of 17 input attributes. Positioning from the offset producers, and dynamic saturations from the closest producer had a higher DOI on water saturation.

Water Saturation Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
Dynamic Attributes			Dynamic Attributes		
1	Oil Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1) (1P)	100
2	Water Saturation (%) (t-1)	100	2	Oil Saturation (%) (t-1) (1P)	100
4	Reservoir Pressure (psi) (t)	23	2		
5	Water Rate (t)	18			
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES					
		15			

Figure 9-5: Scenario 1 – Water Saturation Model Input Attributes

9.2 Production Profile Plots

9.2.1 Entire Reservoir

Figure 9-6: Scenario 1 – Entire Field Production

9.2.2 Good History Match of Production

Figure 9-7: Scenario 1 – Well-003 Production History Match

Figure 9-8: Scenario 1 – Well-007 Production History Match

Well-009

Figure 9-9: Scenario 1 – Well-009 Production History Match

Well-010

Figure 9-10: Scenario 1 – Well-010 Production History Match

Well-015

Figure 9-11: Scenario 1 – Well-015 Production History Match

Well-017

Figure 9-12: Scenario 1 – Well-017 Production History Match

Well-018

Figure 9-13: Scenario 1 – Well-018 Production History Match

Well-020

Figure 9-14: Scenario 1 – Well-020 Production History Match

Well-021

Figure 9-15: Scenario 1 – Well-021 Production History Match

Well-024

Figure 9-16: Scenario 1 – Well-024 Production History Match

Well-025

Figure 9-17: Scenario 1 – Well-025 Production History Match

Well-030

Figure 9-18: Scenario 1 – Well-030 Production History Match

Well-031

Figure 9-19: Scenario 1 – Well-031 Production History Match

Well-035

Figure 9-20: Scenario 1 – Well-035 Production History Match

Well-036

Figure 9-21: Scenario 1 – Well-036 Production History Match

Well-038

Figure 9-22: Scenario 1 – Well-038 Production History Match

Well-040

Figure 9-23: Scenario 1 – Well-040 Production History Match

Well-041

Figure 9-24: Scenario 1 – Well-041 Production History Match

Well-045

Figure 9-25: Scenario 1 – Well-045 Production History Match

Well-046

Figure 9-26: Scenario 1 – Well-046 Production History Match

Well-047

Figure 9-27: Scenario 1 – Well-047 Production History Match

Well-049

Figure 9-28: Scenario 1 – Well-049 Production History Match

Well-050

Figure 9-29: Scenario 1 – Well-050 Production History Match

Well-051

Figure 9-30: Scenario 1 – Well-051 Production History Match

Well-052

Figure 9-31: Scenario 1 – Well-052 Production History Match

Well-053

Figure 9-32: Scenario 1 – Well-053 Production History Match

Well-056

Figure 9-33: Scenario 1 – Well-056 Production History Match

Well-057

Figure 9-34: Scenario 1 – Well-057 Production History Match

9.2.3 Average History Match of Production

Figure 9-35: Scenario 1 – Well-001 Production History Match

Well-002

Figure 9-36: Scenario 1 – Well-002 Production History Match

Well-004

Figure 9-37: Scenario 1 – Well-004 Production History Match

Well-005

Figure 9-38: Scenario 1 – Well-005 Production History Match

Well-006

Figure 9-39: Scenario 1 – Well-006 Production History Match

Well-008

Figure 9-40: Scenario 1 – Well-008 Production History Match

Well-011

Figure 9-41: Scenario 1 – Well-011 Production History Match

Well-012

Figure 9-42: Scenario 1 – Well-012 Production History Match

Well-013

Figure 9-43: Scenario 1 – Well-013 Production History Match

Well-014

Figure 9-44: Scenario 1 – Well-014 Production History Match

Well-016

Figure 9-45: Scenario 1 – Well-016 Production History Match

Well-019

Figure 9-46: Scenario 1 – Well-019 Production History Match

Well-022

Figure 9-47: Scenario 1 – Well-022 Production History Match

Well-023

Figure 9-48: Scenario 1 – Well-023 Production History Match

Well-026

Figure 9-49: Scenario 1 – Well-026 Production History Match

Well-027

Figure 9-50: Scenario 1 – Well-027 Production History Match

Well-028

Figure 9-51: Scenario 1 – Well-028 Production History Match

Well-029

Figure 9-52: Scenario 1 – Well-029 Production History Match

Well-032

Figure 9-53: Scenario 1 – Well-032 Production History Match

Well-033

Figure 9-54: Scenario 1 – Well-033 Production History Match

Well-034

Figure 9-55: Scenario 1 – Well-034 Production History Match

Well-037

Figure 9-56: Scenario 1 – Well-037 Production History Match

Well-039

Figure 9-57: Scenario 1 – Well-039 Production History Match

Well-042

Figure 9-58: Scenario 1 – Well-042 Production History Match

Well-043

Figure 9-59: Scenario 1 – Well-043 Production History Match

Well-044

Figure 9-60: Scenario 1 – Well-044 Production History Match

Well-054

Figure 9-61: Scenario 1 – Well-054 Production History Match

Well-055

Figure 9-62: Scenario 1 – Well-055 Production History Match

9.2.4 Poor History Match of Production

2% of the wells had poor history match when compared to the actual numerical simulation production data.

Figure 9-63: Scenario 1 – Well-048 Production History Match

9.3 Distribution Maps

Distribution maps are presented at different timesteps, including the months of January, June, and December of 2014, and the months of June and December of years 2015 and 2016.

Reservoir Pressure (psi) at 2014-12-31

Water Saturation (%) at 2014-12-31

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Reservoir Pressure (psi) at 2015-12-31

Water Saturation (%) at 2015-12-31

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Reservoir Pressure (psi) at 2016-12-31

Water Saturation (%) at 2016-12-31

Figure 9-64: Scenario 1 – Distribution Maps at Different Timesteps

10 Appendix D: Scenario 2 – Mixed Partitioning TDM (1 Year Validation)

10.1 Input Attributes

The number of input attributes used in the development of each data-driven model was based on KPI analysis and domain expertise. The following tables provide a list of static and dynamic attributes for both the focal and offset wells. Each table is composed of three columns that indicate the ranking, name of the input attribute, and its degree of influence (DOI) with respect to the output model.

10.1.1 Oil Predictive Model

Oil Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			5	TVD (ft)(1I)	73
			6	Top (ft)(2P)	65
			9	TVD (ft)(1P)	55
			11	Pay thickness (ft)(1P)	50
			7		
Dynamic Attributes			Dynamic Attributes		
1	Oil Rate (t-1)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Gas Rate (t-1)	100	3	FBH Pressure (psi)(t-1)(1I)	96
3	Permeability I(t-1)	49	4	Reservoir Pressure (psi)(t-1)(1I)	96
4	Time	48	5	Distance(t)(2P)	96
4			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			12	Distance (t)(1P)	61
			34	Distance(t)(1I)	28
			11		
TOTAL ATTRIBUTES		24			

Figure 10-1: Scenario 2 – Oil Model Input Attributes

10.1.2 Gas Predictive Model

Gas Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			4	X/Longitude(1I)	84
Dynamic Attributes			5	TVD (ft)(1I)	73
1	Oil Rate (t)	100	8	Y/Latitude(1I)	56
2	Oil Rate (t-1)	60	6		
3	Gas Rate (t-1)	60			
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
			2	Distance(t-1)(2P)	97
TOTAL ATTRIBUTES			3	FBH Pressure (psi)(t-1)(1I)	96
		22	4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Figure 10-2: Scenario 2 – Gas Model Input Attributes

10.1.3 Water Predictive Model

Water Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
2	X/Longitude	89	1	X/Longitude(2P)	100
3	Top (ft)	84	2	Top (ft)(2P)	90
9	Porosity (%)	1	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
Dynamic Attributes			5	X/Longitude(2I)	75
1	q(t-1)-Water	100	7	TVD (ft)(2I)	65
2	Oil Saturation (%) (t-1)	78	6		
3	Water Saturation (%) (t-1)	78	Dynamic Attributes		
4	Permeability I(t-1)	72	1	Water Saturation (%) (t-1)(1P)	100
15	Oil Rate (t)	1	2	Oil Saturation (%) (t-1)(1P)	100
16	Gas Rate (t)	1	3	Distance(t)(1I)	92
6			12	Permeability I(t-1)(2P)	42
TOTAL ATTRIBUTES			15	Permeability I(t-1)(2I)	39
20			5		

Figure 10-3: Scenario 2 – Water Model Input Attributes

10.1.4 Reservoir Pressure Predictive Model

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
			4	Top (ft)(1I)	85
Dynamic Attributes			5	Top (ft)(2P)	79
1	Reservoir Pressure (psi)(t-1)	100	6	Pay thickness (ft)(1I)	79
2	FBH Pressure (psi)(t)	78	6		
3	FBH Pressure (psi)(t-1)	52			
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
			3		
TOTAL ATTRIBUTES		17			

Figure 10-4: Scenario 2 – Reservoir Pressure Model Input Attributes

10.1.5 Water Saturation Predictive Model

Water Saturation Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
Dynamic Attributes			Dynamic Attributes		
1	Oil Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1) (1P)	100
2	Water Saturation (%) (t-1)	100	2	Oil Saturation (%) (t-1) (1P)	100
4	Reservoir Pressure (psi) (t)	23	2		
5	Water Rate (t)	18			
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES		15			

Figure 10-5: Scenario 2 – Water Saturation Model Input Attributes

10.2 Production Profile Plots

10.2.1 Entire Reservoir

Figure 10-6: Scenario 2 – Entire Field Production

10.2.2 Good History Match of Production

The following wells had excellent if not close history matches for oil, gas, and water production. The TDM predictions follow the actual production trend and have established a good relationship between input and output attributes.

Figure 10-7: Scenario 2 – Well-002 Production History Match

Well-004

Figure 10-8: Scenario 2 – Well-004 Production History Match

Well-006

Figure 10-9: Scenario 2 – Well-006 Production History Match

Well-007

Figure 10-10: Scenario 2 – Well-007 Production History Match

Well-009

Figure 10-11: Scenario 2 – Well-009 Production History Match

Well-010

Figure 10-12: Scenario 2 – Well-010 Production History Match

Well-012

Figure 10-13: Scenario 2 – Well-012 Production History Match

Well-013

Figure 10-14: Scenario 2 – Well-013 Production History Match

Well-015

Figure 10-15: Scenario 2 – Well-015 Production History Match

Well-017

Figure 10-16: Scenario 2 – Well-017 Production History Match

Well-022

Figure 10-17: Scenario 2 – Well-022 Production History Match

Well-024

Figure 10-18: Scenario 2 – Well-024 Production History Match

Well-025

Figure 10-19: Scenario 2 – Well-025 Production History Match

Well-027

Figure 10-20: Scenario 2 – Well-027 Production History Match

Well-030

Figure 10-21: Scenario 2 – Well-030 Production History Match

Well-031

Figure 10-22: Scenario 2 – Well-031 Production History Match

Well-033

Figure 10-23: Scenario 2 – Well-033 Production History Match

Well-035

Figure 10-24: Scenario 2 – Well-035 Production History Match

Well-041

Figure 10-25: Scenario 2 – Well-041 Production History Match

Well-045

Figure 10-26: Scenario 2 – Well-045 Production History Match

Well-046

Figure 10-27: Scenario 2 – Well-046 Production History Match

Well-047

Figure 10-28: Scenario 2 – Well-047 Production History Match

Well-050

Figure 10-29: Scenario 2 – Well-050 Production History Match

Well-051

Figure 10-30: Scenario 2 – Well-051 Production History Match

Well-052

Figure 10-31: Scenario 2 – Well-052 Production History Match

Well-053

Figure 10-32: Scenario 2 – Well-053 Production History Match

Well-055

Figure 10-33: Scenario 2 – Well-055 Production History Match

Well-057

Figure 10-34: Scenario 2 – Well-057 Production History Match

10.2.3 Average History Match of Production

Well-001

Figure 10-35: Scenario 2 – Well-001 Production History Match

Well-003

Figure 10-36: Scenario 2 – Well-003 Production History Match

Well-005

Figure 10-37: Scenario 2 – Well-005 Production History Match

Well-008

Figure 10-38: Scenario 2 – Well-008 Production History Match

Well-011

Figure 10-39: Scenario 2 – Well-011 Production History Match

Well-014

Figure 10-40: Scenario 2 – Well-014 Production History Match

Well-018

Figure 10-41: Scenario 2 – Well-018 Production History Match

Well-019

Figure 10-42: Scenario 2 – Well-019 Production History Match

Well-020

Figure 10-43: Scenario 2 – Well-020 Production History Match

Well-021

Figure 10-44: Scenario 2 – Well-021 Production History Match

Well-023

Figure 10-45: Scenario 2 – Well-023 Production History Match

Well-026

Figure 10-46: Scenario 2 – Well-026 Production History Match

Well-028

Figure 10-47: Scenario 2 – Well-028 Production History Match

Well-029

Figure 10-48: Scenario 2 – Well-029 Production History Match

Well-032

Figure 10-49: Scenario 2 – Well-032 Production History Match

Well-034

Figure 10-50: Scenario 2 – Well-034 Production History Match

Well-036

Figure 10-51: Scenario 2 – Well-036 Production History Match

Well-037

Figure 10-52: Scenario 2 – Well-037 Production History Match

Well-038

Figure 10-53: Scenario 2 – Well-038 Production History Match

Well-039

Figure 10-54: Scenario 2 – Well-039 Production History Match

Well-040

Figure 10-55: Scenario 2 – Well-040 Production History Match

Well-042

Figure 10-56: Scenario 2 – Well-042 Production History Match

Well-043

Figure 10-57: Scenario 2 – Well-043 Production History Match

Well-044

Figure 10-58: Scenario 2 – Well-044 Production History Match

Well-049

Figure 10-59: Scenario 2 – Well-049 Production History Match

Well-054

Figure 10-60: Scenario 2 – Well-054 Production History Match

Well-056

Figure 10-61: Scenario 2 – Well-056 Production History Match

10.2.4 Poor History Match of Production

The water predictions from well-016 are significantly distant from the actual water production. Although the oil predictions are close to the actual oil production, the oil trend is decreasing rather than fluctuating. The combination of the oil and water predictions result in an overall poor history match.

Although the oil and water predictions of well-048 follow the actual production trend, these are inconsistent trend at the beginning and at the end of the well's life.

Figure 10-62: Scenario 2 – Well-016 Production History Match

Well-048

Figure 10-63: Scenario 2 – Well-048 Production History Match

10.3 Distribution Maps

Distribution maps are presented at different timesteps, including the months of January, June, and December of 2014, and the months of June and December of years 2015 and 2016.

Reservoir Pressure (psi) at 2014-01-31

Water Saturation (%) at 2014-01-31

Reservoir Pressure (psi) at 2014-06-30

Water Saturation (%) at 2014-06-30

Reservoir Pressure (psi) at 2014-12-31

Water Saturation (%) at 2014-12-31

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Reservoir Pressure (psi) at 2015-12-31

Water Saturation (%) at 2015-12-31

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Figure 10-64: Scenario 2 – Distribution Maps at Different Timesteps

11 Appendix E: Scenario 3: Mixed Partitioning TDM (2 Year Validation)

11.1 Input Attributes

The number of input attributes used in the development of each data-driven model was based on KPI analysis and domain expertise. The following tables provide a list of static and dynamic attributes for both the focal and offset wells. Each table is composed of three columns that indicate the ranking, name of the input attribute, and its degree of influence (DOI) with respect to the output model.

11.1.1 Oil Predictive Model

Oil Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
5	TVD(ft)	73	3	Top (ft)(1I)	90
3			5	TVD (ft)(1I)	73
			6	Top (ft)(2P)	65
Dynamic Attributes			9	TVD (ft)(1P)	55
1	Oil Rate (t-1)	100	10	X/Longitude(1P)	52
2	Gas Rate (t-1)	100	11	Pay thickness (ft)(1P)	50
3	Permeability I(t-1)	49	8		
4	Time	48	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
TOTAL ATTRIBUTES			2	Distance(t-1)(2P)	97
		25	3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Figure 11-1: Scenario 3 – Oil Model Input Attributes

11.1.2 Gas Predictive Model

Gas Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			4	X/Longitude(1I)	84
			5	TVD (ft)(1I)	73
			5		
Dynamic Attributes			Dynamic Attributes		
1	Oil Rate (t)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Oil Rate (t-1)	60	2	Distance(t-1)(2P)	97
3	Gas Rate (t-1)	60	3	FBH Pressure (psi)(t-1)(1I)	96
4	Permeability I(t-1)	29	4	Reservoir Pressure (psi)(t-1)(1I)	96
4			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		
TOTAL ATTRIBUTES		21			

Figure 11-2: Scenario 3 – Gas Model Input Attributes

11.1.3 Water Predictive Model

Water Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
			5	X/Longitude(2I)	75
			7	TVD (ft)(2I)	65
			6		
Dynamic Attributes			Dynamic Attributes		
1	q(t-1)- Water	100	1	Water Saturation (t-1)(1P)	100
2	Oil Saturation (t-1)	78	2	Oil Saturation (t-1)(1P)	100
3	Water Saturation (t-1)	78	3	Distance(t)(1I)	92
4	Permeability I(t-1)	72	12	Permeability I(t-1)(2P)	42
15	Oil Rate (t)	1	15	Permeability I(t-1)(2I)	39
16	Gas Rate (t)	1	5		
6					
TOTAL ATTRIBUTES		20			

Figure 11-3: Scenario 3 – Water Model Input Attributes

11.1.4 Reservoir Pressure Predictive Model

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
			4	Top (ft)(1I)	85
Dynamic Attributes			5	Top (ft)(2P)	79
1	Reservoir Pressure (psi)(t-1)	100	6	Pay thickness (ft)(1I)	79
2	FBH Pressure (psi)(t)	78	6		
3	FBH Pressure (psi)(t-1)	52			
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
			3		
TOTAL ATTRIBUTES		17			

Figure 11-4: Scenario 3 – Reservoir Pressure Model Input Attributes

11.1.5 Water Saturation Predictive Model

Water Saturation Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
			4		
Dynamic Attributes			Dynamic Attributes		
1	Oil Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1) (1P)	100
2	Water Saturation (%) (t-1)	100	2	Oil Saturation (%) (t-1) (1P)	100
4	Reservoir Pressure (psi) (t)	23	2		
5	Water Rate (t)	18			
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES		15			

Figure 11-5: Scenario 3 – Water Saturation Model Input Attributes

11.2 Production Profile Plots

11.2.1 Entire Reservoir

Entire Reservoir

Figure 11-6: Scenario 3 – Entire Field Production

11.2.2 Good History Match of Production

Figure 11-7: Scenario 3 – Well-002 Production History Match

Figure 11-8: Scenario 3 – Well-004 Production History Match

Figure 11-9: Scenario 3 – Well-006 Production History Match

Figure 11-10: Scenario 3 – Well-007 Production History Match

Well-009

Figure 11-11: Scenario 3 – Well-009 Production History Match

Well-010

Figure 11-12: Scenario 3 – Well-010 Production History Match

Well-015

Figure 11-13: Scenario 3 – Well-015 Production History Match

Well-017

Figure 11-14: Scenario 3 – Well-017 Production History Match

Well-019

Figure 11-15: Scenario 3 – Well-019 Production History Match

Well-025

Figure 11-16: Scenario 3 – Well-025 Production History Match

Well-030

Figure 11-17: Scenario 3 – Well-030 Production History Match

Well-031

Figure 11-18: Scenario 3 – Well-031 Production History Match

Well-035

Figure 11-19: Scenario 3 – Well-035 Production History Match

Well-039

Figure 11-20: Scenario 3 – Well-039 Production History Match

Well-041

Figure 11-21: Scenario 3 – Well-041 Production History Match

Well-045

Figure 11-22: Scenario 3 – Well-045 Production History Match

Well-046

Figure 11-23: Scenario 3 – Well-046 Production History Match

Well-047

Figure 11-24: Scenario 3 – Well-047 Production History Match

Well-050

Figure 11-25: Scenario 3 – Well-050 Production History Match

Well-051

Figure 11-26: Scenario 3 – Well-051 Production History Match

Well-055

Figure 11-27: Scenario 3 – Well-055 Production History Match

Well-057

Figure 11-28: Scenario 3 – Well-057 Production History Match

11.2.3 Average History Match of Production

Figure 11-29: Scenario 3 – Well-001 Production History Match

Figure 11-30: Scenario 3 – Well-003 Production History Match

Well-005

Figure 11-31: Scenario 3 – Well-005 Production History Match

Well-008

Figure 11-32: Scenario 3 – Well-008 Production History Match

Well-011

Figure 11-33: Scenario 3 – Well-011 Production History Match

Well-012

Figure 11-34: Scenario 3 – Well-012 Production History Match

Well-013

Figure 11-35: Scenario 3 – Well-013 Production History Match

Well-014

Figure 11-36: Scenario 3 – Well-014 Production History Match

Well-016

Figure 11-37: Scenario 3 – Well-016 Production History Match

Well-018

Figure 11-38: Scenario 3 – Well-018 Production History Match

Well-020

Figure 11-39: Scenario 3 – Well-020 Production History Match

Well-021

Figure 11-40: Scenario 3 – Well-021 Production History Match

Well-022

Figure 11-41: Scenario 3 – Well-022 Production History Match

Well-023

Figure 11-42: Scenario 3 – Well-023 Production History Match

Well-024

Figure 11-43: Scenario 3 – Well-024 Production History Match

Well-026

Figure 11-44: Scenario 3 – Well-026 Production History Match

Well-027

Figure 11-45: Scenario 3 – Well-027 Production History Match

Well-028

Figure 11-46: Scenario 3 – Well-028 Production History Match

Well-029

Figure 11-47: Scenario 3 – Well-029 Production History Match

Well-032

Figure 11-48: Scenario 3 – Well-032 Production History Match

Well-033

Figure 11-49: Scenario 3 – Well-033 Production History Match

Well-034

Figure 11-50: Scenario 3 – Well-034 Production History Match

Well-037

Figure 11-51: Scenario 3 – Well-037 Production History Match

Well-038

Figure 11-52: Scenario 3 – Well-038 Production History Match

Well-040

Figure 11-53: Scenario 3 – Well-040 Production History Match

Well-042

Figure 11-54: Scenario 3 – Well-042 Production History Match

Well-043

Figure 11-55: Scenario 3 – Well-043 Production History Match

Well-044

Figure 11-56: Scenario 3 – Well-044 Production History Match

Well-049

Figure 11-57: Scenario 3 – Well-049 Production History Match

Well-052

Figure 11-58: Scenario 3 – Well-052 Production History Match

Well-053

Figure 11-59: Scenario 3 – Well-053 Production History Match

Well-056

Figure 11-60: Scenario 3 – Well-056 Production History Match

11.2.4 Poor History Match of Production

Figure 11-61: Scenario 3 – Well-036 Production History Match

Figure 11-62: Scenario 3 – Well-048 Production History Match

Well-054

Figure 11-63: Scenario 3 – Well-054 Production History Match

11.3 Distribution Maps

Distribution maps are presented at different timesteps, including the months of January, June, and December of 2014, and the months of June and December of years 2015 and 2016.

Reservoir Pressure (psi) at 2014-01-31

Water Saturation (%) at 2014-01-31

Reservoir Pressure (psi) at 2014-06-30

Water Saturation (%) at 2014-06-30

Reservoir Pressure (psi) at 2014-12-31

Water Saturation (%) at 2014-12-31

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Reservoir Pressure (psi) at 2015-12-31

Water Saturation (%) at 2015-12-31

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Figure 11-64: Scenario 3 – Distribution Maps at Different Timesteps

12 Appendix F: Scenario 4 – Mixed Partitioning TDM (1 Year Forecast)

12.1 Input Attributes

The number of input attributes used in the development of each data-driven model was based on KPI analysis and domain expertise. The following tables provide a list of static and dynamic attributes for both the focal and offset wells. Each table is composed of three columns that indicate the ranking, name of the input attribute, and its degree of influence (DOI) with respect to the output model.

12.1.1 Oil Predictive Model

Oil Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(1I)	91
2	Porosity (%)	90	3	Top (ft)(1I)	90
5	TVD(ft)	73	4	X/Longitude(1I)	84
3			5	TVD (ft)(1I)	73
			6	Top (ft)(2P)	65
Dynamic Attributes			7	Y/Latitude(1P)	59
1	Oil Rate (t-1)	100	8	Y/Latitude(1I)	56
2	Gas Rate (t-1)	100	9	TVD (ft)(1P)	55
3	Permeability I(t-1)	49	10	X/Longitude(1P)	52
4	Time	48	11	Pay thickness (ft)(1P)	50
9	Completion (ft)(t)	12	16	TVD (ft)(2P)	36
10	Completion (ft)(t-1)	10	20	Y/Latitude(2I)	30
6			30	Pay thickness (ft)(2P)	12
			38	X/Longitude(2I)	4
TOTAL ATTRIBUTES	33		14		
			Dynamic Attributes		
			1	FBH Pressure (psi)(t)(1I)	100
			2	Distance(t-1)(2P)	97
			3	FBH Pressure (psi)(t-1)(1I)	96
			4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			39	Completion (ft)(t)(1P)	14
			40	Completion (ft)(t-1)(1P)	13
			10		

Figure 12-1: Scenario 4 – Oil Model Input Attributes

12.1.2 Gas Predictive Model

Gas Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			4	X/Longitude(1I)	84
			5	TVD (ft)(1I)	73
			8	Y/Latitude(1I)	56
			6		
Dynamic Attributes			Dynamic Attributes		
1	Oil Rate (t)	100	1	FBH Pressure (psi)(t)(1I)	100
2	Oil Rate (t-1)	60	2	Distance(t-1)(2P)	97
3	Gas Rate (t-1)	60	3	FBH Pressure (psi)(t-1)(1I)	96
4	Permeability I(t-1)	29	4	Reservoir Pressure (psi)(t-1)(1I)	96
4			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		
TOTAL ATTRIBUTES		22			

Figure 12-2: Scenario 4 – Gas Model Input Attributes

12.1.3 Water Predictive Model

Water Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
			5	X/Longitude(2I)	75
			7	TVD (ft)(2I)	65
			6		
Dynamic Attributes			Dynamic Attributes		
1	q(t-1)-Water	100	1	Water Saturation (°)(t-1)(1P)	100
2	Oil Saturation (°)(t-1)	78	2	Oil Saturation (°)(t-1)(1P)	100
3	Water Saturation (°)(t-1)	78	3	Distance(t)(1I)	92
4	Permeability I(t-1)	72	12	Permeability I(t-1)(2P)	42
15	Oil Rate (t)	1	15	Permeability I(t-1)(2I)	39
16	Gas Rate (t)	1	5		
6					
TOTAL ATTRIBUTES		20			

Figure 12-3: Scenario 4 – Water Model Input Attributes

12.1.4 Reservoir Pressure Predictive Model

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
	0		12	Porh(1-sw)(1I)	58
			15	Pay thickness (ft)(2I)	45
			21	Permeability (md)(1I)	25
			23	Pay thickness (ft)(2P)	24
			31	Pay thickness (ft)(1P)	15
			5		
Dynamic Attributes			Dynamic Attributes		
1	Reservoir Pressure (psi)(t-1)	100	1	Reservoir Pressure (psi)(t-1)(1P)	100
2	FBH Pressure (psi)(t)	78	3	FBH Pressure (psi)(t)(1P)	90
4	Oil Saturation (%) (t-1)	40	6	Reservoir Pressure (psi)(t-1)(2P)	56
5	Water Saturation (%) (t-1)	40	7	FBH Pressure (psi)(t)(2P)	45
7	Permeability I(t-1)	18	9	Distance(t)(2I)	34
12	Oil Rate (t-1)	5	11	Distance(t)(1I)	31
13	Oil Rate (t)	4	13	Water Saturation (%) (t-1)(2P)	24
14	Gas Rate (t)	4	14	Oil Saturation (%) (t-1)(2P)	24
17	Oil Rate (t-1)	3	19	FBH Pressure (psi)(t)(2I)	16
9			21	Reservoir Pressure (psi)(t-1)(2I)	16
			24	Permeability I(t-1)(2I)	14
TOTAL ATTRIBUTES	33		26	Water Injection Rate(t)(1I)	11
			31	Distance(t)(1P)	10
			39	Reservoir Pressure (psi)(t-1)(1I)	8
			40	FBH Pressure (psi)(t)(1I)	7
			44	Completion (ft)(t)(1P)	6
			46	Distance(t)(2P)	6
			51	Water Saturation (%) (t-1)(2I)	5
			52	Oil Saturation (%) (t-1)(2I)	5
			19		

Figure 12-4: Scenario 4 – Reservoir Pressure Model Input Attributes

12.1.5 Water Saturation Predictive Model

Water Saturation Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
3	Y/Latitude	65	36	Permeability (md)(1I)	4
5	Porh(1-sw)	26	1		
7	Porosity (%)	22			
2			Dynamic Attributes		
			5	Distance(t)(1I)	50
Dynamic Attributes			9	Distance(t)(2I)	46
1	Oil Saturation (%) (t-1)	100	28	Water Saturation (%) (t-1)(1I)	20
2	Water Saturation (%) (t-1)	100	29	Oil Saturation (%) (t-1)(1I)	20
4	Reservoir Pressure (psi)(t)	23	30	Distance(t)(1P)	19
5	Water Rate (t)	18	32	Water Saturation (%) (t-1)(2I)	18
10	Oil Rate (t)	8	33	Oil Saturation (%) (t-1)(2I)	18
11	Gas Rate (t)	8	35	Distance(t)(2P)	17
6			36	Permeability I(t-1)(1P)	16
			43	Permeability I(t-1)(2P)	14
TOTAL ATTRIBUTES		20	48	Permeability I(t-1)(1I)	8
			11		

Figure 12-5: Scenario 4 – Water Saturation Model Input Attributes

12.2 Production Profile Plots

12.2.1 Entire Reservoir

Entire Reservoir

Figure 12-6: Scenario 4 – Entire Field Production

12.2.2 Good History Match of Production

Figure 12-7: Scenario 4 – Well-001 Production History Match

Figure 12-8: Scenario 4 – Well-003 Production History Match

Figure 12-9: Scenario 4 – Well-006 Production History Match

Figure 12-10: Scenario 4 – Well-009 Production History Match

Figure 12-11: Scenario 4 – Well-010 Production History Match

Figure 12-12: Scenario 4 – Well-013 Production History Match

Well-014

Figure 12-13: Scenario 4 – Well-014 Production History Match

Well-015

Figure 12-14: Scenario 4 – Well-015 Production History Match

Well-018

Figure 12-15: Scenario 4 – Well-018 Production History Match

Well-019

Figure 12-16: Scenario 4 – Well-019 Production History Match

Well-020

Figure 12-17: Scenario 4 – Well-020 Production History Match

Well-022

Figure 12-18: Scenario 4 – Well-022 Production History Match

Well-023

Figure 12-19: Scenario 4 – Well-023 Production History Match

Well-024

Figure 12-20: Scenario 4 – Well-024 Production History Match

Well-025

Figure 12-21: Scenario 4 – Well-025 Production History Match

Well-027

Figure 12-22: Scenario 4 – Well-027 Production History Match

Well-029

Figure 12-23: Scenario 4 – Well-029 Production History Match

Well-030

Figure 12-24: Scenario 4 – Well-030 Production History Match

Well-031

Figure 12-25: Scenario 4 – Well-031 Production History Match

Well-033

Figure 12-26: Scenario 4 – Well-033 Production History Match

Well-034

Figure 12-27: Scenario 4 – Well-034 Production History Match

Well-035

Figure 12-28: Scenario 4 – Well-035 Production History Match

Well-036

Figure 12-29: Scenario 4 – Well-036 Production History Match

Well-038

Figure 12-30: Scenario 4 – Well-038 Production History Match

Well-040

Figure 12-31: Scenario 4 – Well-040 Production History Match

Well-041

Figure 12-32: Scenario 4 – Well-041 Production History Match

Well-042

Figure 12-33: Scenario 4 – Well-042 Production History Match

Well-043

Figure 12-34: Scenario 4 – Well-043 Production History Match

Well-045

Figure 12-35: Scenario 4 – Well-045 Production History Match

Well-047

Figure 12-36: Scenario 4 – Well-047 Production History Match

Well-048

Figure 12-37: Scenario 4 – Well-048 Production History Match

Well-049

Figure 12-38: Scenario 4 – Well-049 Production History Match

Well-050

Figure 12-39: Scenario 4 – Well-050 Production History Match

Well-051

Figure 12-40: Scenario 4 – Well-051 Production History Match

Well-052

Figure 12-41: Scenario 4 – Well-052 Production History Match

Well-053

Figure 12-42: Scenario 4 – Well-053 Production History Match

Well-054

Figure 12-43: Scenario 4 – Well-054 Production History Match

Well-055

Figure 12-44: Scenario 4 – Well-055 Production History Match

Well-056

Figure 12-45: Scenario 4 – Well-056 Production History Match

Well-057

Figure 12-46: Scenario 4 – Well-057 Production History Match

12.2.3 Average History Match of Production

Figure 12-47: Scenario 4 – Well-002 Production History Match

Figure 12-48: Scenario 4 – Well-004 Production History Match

Well-005

Figure 12-49: Scenario 4 – Well-005 Production History Match

Well-007

Figure 12-50: Scenario 4 – Well-007 Production History Match

Well-008

Figure 12-51: Scenario 4 – Well-008 Production History Match

Well-012

Figure 12-52: Scenario 4 – Well-012 Production History Match

Well-016

Figure 12-53: Scenario 4 – Well-016 Production History Match

Well-017

Figure 12-54: Scenario 4 – Well-017 Production History Match

Well-021

Figure 12-55: Scenario 4 – Well-021 Production History Match

Well-026

Figure 12-56: Scenario 4 – Well-026 Production History Match

Well-028

Figure 12-57: Scenario 4 – Well-028 Production History Match

Well-032

Figure 12-58: Scenario 4 – Well-032 Production History Match

Well-037

Figure 12-59: Scenario 4 – Well-037 Production History Match

Well-039

Figure 12-60: Scenario 4 – Well-039 Production History Match

Well-044

Figure 12-61: Scenario 4 – Well-044 Production History Match

Well-046

Figure 12-62: Scenario 4 – Well-046 Production History Match

12.2.4 Poor History Match of Production

Poor results were not visually inspected during the blind history match time period.

12.2.5 Good Forecast Production

Figure 12-63: Scenario 4 – Well-002 Forecast Production

Figure 12-64: Scenario 4 – Well-010 Forecast Production

Well-013

Figure 12-65: Scenario 4 – Well-013 Forecast Production

Well-019

Figure 12-66: Scenario 4 – Well-019 Forecast Production

Figure 12-67: Scenario 4 – Well-022 Forecast Production

Figure 12-68: Scenario 4 – Well-023 Forecast Production

Well-024

Figure 12-69: Scenario 4 – Well-024 Forecast Production

Well-048

Figure 12-70: Scenario 4 – Well-048 Forecast Production

Well-053

Figure 12-71: Scenario 4 – Well-053 Forecast Production

Well-057

Figure 12-72: Scenario 4 – Well-057 Forecast Production

12.2.6 Average Forecast Production

Figure 12-73: Scenario 4 – Well-017 Forecast Production

Figure 12-74: Scenario 4 – Well-025 Forecast Production

Well-027

Figure 12-75: Scenario 4 – Well-027 Forecast Production

Well-031

Figure 12-76: Scenario 4 – Well-031 Forecast Production

Well-034

Figure 12-77: Scenario 4 – Well-034 Forecast Production

Well-041

Figure 12-78: Scenario 4 – Well-041 Forecast Production

Well-042

Figure 12-79: Scenario 4 – Well-042 Forecast Production

Well-043

Figure 12-80: Scenario 4 – Well-043 Forecast Production

Well-047

Figure 12-81: Scenario 4 – Well-047 Forecast Production

Well-049

Figure 12-82: Scenario 4 – Well-049 Forecast Production

Well-051

Figure 12-83: Scenario 4 – Well-051 Forecast Production

12.2.7 Poor Forecast Production

Figure 12-84: Scenario 4 – Well-003 Forecast Production

Figure 12-85: Scenario 4 – Well-015 Forecast Production

Well-032

Figure 12-86: Scenario 4 – Well-032 Forecast Production

Well-036

Figure 12-87: Scenario 4 – Well-036 Forecast Production

Well-038

Figure 12-88: Scenario 4 – Well-038 Forecast Production

Well-039

Figure 12-89: Scenario 4 – Well-039 Forecast Production

Well-040

Figure 12-90: Scenario 4 – Well-040 Forecast Production

Well-044

Figure 12-91: Scenario 4 – Well-044 Forecast Production

Well-050

Figure 12-92: Scenario 4 – Well-050 Forecast Production

Well-052

Figure 12-93: Scenario 4 – Well-052 Forecast Production

Well-054

Figure 12-94: Scenario 4 – Well-054 Forecast Production

Well-055

Figure 12-95: Scenario 4 – Well-055 Forecast Production

Well-056

Figure 12-96: Scenario 4 – Well-056 Forecast Production

12.3 Distributions Maps

Distribution maps are presented at different timesteps, including the beginning, middle, and end of the year.

Reservoir Pressure (psi) at 2014-12-31

Water Saturation (%) at 2014-12-31

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Reservoir Pressure (psi) at 2015-12-31

Water Saturation (%) at 2015-12-31

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Figure 12-97: Scenario 4 – Distribution Maps at Different Timesteps

13 Appendix G: Scenario 5 – Mixed Partitioning (2 Year Forecast)

13.1 Input Attributes

The number of input attributes used in the development of each data-driven model was based on KPI analysis and domain expertise. The following tables provide a list of static and dynamic attributes for both the focal and offset wells. Each table is composed of three columns that indicate the ranking, name of the input attribute, and its degree of influence (DOI) with respect to the output model.

13.1.1 Oil Predictive Model

Oil Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	2	Porh(1-sw)(1I)	91
2	Porosity (%)	90	3	Top (ft)(1I)	90
5	TVD(ft)	73	5	TVD (ft)(1I)	73
3			6	Top (ft)(2P)	65
			9	TVD (ft)(1P)	55
Dynamic Attributes			10	X/Longitude(1P)	52
1	Oil Rate (t-1)	100	11	Pay thickness (ft)(1P)	50
2	Gas Rate (t-1)	100	7		
3	Permeability I(t-1)	49	Dynamic Attributes		
4	Time	48	1	FBH Pressure (psi)(t)(1I)	100
9	Completion (ft)(t)	12	2	Distance(t-1)(2P)	97
5			3	FBH Pressure (psi)(t-1)(1I)	96
TOTAL ATTRIBUTES		25	4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Figure 13-1: Scenario 5 – Oil Model Input Attributes

13.1.2 Gas Predictive Model

Gas Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Porh(1-sw)	100	1	Completion (ft)(1P)	100
2	Porosity (%)	90	2	Porh(1-sw)(1I)	91
2			3	Top (ft)(1I)	90
			4	X/Longitude(1I)	84
Dynamic Attributes			5	TVD (ft)(1I)	73
1	Oil Rate (t)	100	8	Y/Latitude(1I)	56
2	Oil Rate (t-1)	60	6		
3	Gas Rate (t-1)	60			
4	Permeability I(t-1)	29	Dynamic Attributes		
4			1	FBH Pressure (psi)(t)(1I)	100
			2	Distance(t-1)(2P)	97
TOTAL ATTRIBUTES			3	FBH Pressure (psi)(t-1)(1I)	96
		22	4	Reservoir Pressure (psi)(t-1)(1I)	96
			5	Distance(t)(2P)	96
			6	FBH Pressure (psi)(t)(2I)	93
			7	FBH Pressure (psi)(t-1)(2I)	92
			8	Reservoir Pressure (psi)(t-1)(2I)	92
			9	Water Saturation (%) (t-1)(2I)	87
			10	Oil Saturation (%) (t-1)(2I)	87
			10		

Figure 13-2: Scenario 5 – Gas Model Input Attributes

13.1.3 Water Predictive Model

Water Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Permeability (md)	100	1	X/Longitude(2P)	100
2	X/Longitude	89	2	Top (ft)(2P)	90
3	Top (ft)	84	3	TVD (ft)(2P)	86
3			4	Top (ft)(2I)	79
			5	X/Longitude(2I)	75
			7	TVD (ft)(2I)	65
			6		
Dynamic Attributes			Dynamic Attributes		
1	q(t-1)-Water	100	1	Water Saturation (°)(t-1)(1P)	100
2	Oil Saturation (°)(t-1)	78	2	Oil Saturation (°)(t-1)(1P)	100
3	Water Saturation (°)(t-1)	78	3	Distance(t)(1I)	92
4	Permeability I(t-1)	72	12	Permeability I(t-1)(2P)	42
15	Oil Rate (t-1)	1	15	Permeability I(t-1)(2I)	39
16	Gas Rate (t-1)	1	5		
6					
TOTAL ATTRIBUTES		20			

Figure 13-3: Scenario 5 – Water Model Input Attributes

13.1.4 Reservoir Pressure Predictive Model

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	X/Longitude	100	1	X/Longitude(1P)	100
2	Top (ft)	81	2	X/Longitude(1I)	88
2			3	X/Longitude(2P)	88
			4	Top (ft)(1I)	85
Dynamic Attributes			5	Top (ft)(2P)	79
1	Reservoir Pressure (psi)(t-1)	100	6	Pay thickness (ft)(1I)	79
2	FBH Pressure (psi)(t)	78	6		
3	FBH Pressure (psi)(t-1)	52			
12	Water Rate (t)	5	Dynamic Attributes		
13	Oil Rate (t)	4	1	Reservoir Pressure (psi)(t-1)(1P)	100
14	Gas Rate (t)	4	2	FBH Pressure (psi)(t-1)(1P)	91
6			3	FBH Pressure (psi)(t)(1P)	90
			3		
TOTAL ATTRIBUTES		17			

Figure 13-4: Scenario 5 – Reservoir Pressure Model Input Attributes

13.1.5 Water Saturation Predictive Model

Reservoir Pressure Model – Input Attributes

FOCAL WELL			OFFSET WELLS		
Static Attributes			Static Attributes		
Rank	Attribute	DOI	Rank	Attribute	DOI
1	Top (ft)	100	1	X/Longitude(2P)	100
2	X/Longitude	87	2	Top (ft)(2P)	97
3	Y/Latitude	65	3	Y/Latitude(1P)	79
3			4	X/Longitude(1P)	74
			4		
Dynamic Attributes			Dynamic Attributes		
1	Oil Saturation (%) (t-1)	100	1	Water Saturation (%) (t-1)(1P)	100
2	Water Saturation (%) (t-1)	100	2	Oil Saturation (%) (t-1)(1P)	100
4	Reservoir Pressure (psi)(t)	23	2		
5	Water Rate (t)	18			
10	Oil Rate (t)	8			
11	Gas Rate (t)	8			
6					
TOTAL ATTRIBUTES		15			

Figure 13-5: Scenario 5 – Water Saturation Model Input Attributes

13.2 Production Profile Plots

13.2.1 Entire Reservoir

Entire Reservoir

Figure 13-6: Scenario 5 – Entire Field Production

13.2.2 Good History Match Production

Figure 13-7: Scenario 5 – Well-002 Production History Match

Figure 13-8: Scenario 5 – Well-007 Production History Match

Well-009

Figure 13-9: Scenario 5 – Well-009 Production History Match

Well-010

Figure 13-10: Scenario 5 – Well-010 Production History Match

Well-013

Figure 13-11: Scenario 5 – Well-013 Production History Match

Well-015

Figure 13-12: Scenario 5 – Well-015 Production History Match

Well-018

Figure 13-13: Scenario 5 – Well-018 Production History Match

Well-019

Figure 13-14: Scenario 5 – Well-019 Production History Match

Well-020

Figure 13-15: Scenario 5 – Well-020 Production History Match

Well-021

Figure 13-16: Scenario 5 – Well-021 Production History Match

Well-022

Figure 13-17: Scenario 5 – Well-022 Production History Match

Well-023

Figure 13-18: Scenario 5 – Well-023 Production History Match

Well-024

Figure 13-19: Scenario 5 – Well-024 Production History Match

Well-025

Figure 13-20: Scenario 5 – Well-025 Production History Match

Well-027

Figure 13-21: Scenario 5 – Well-027 Production History Match

Well-030

Figure 13-22: Scenario 5 – Well-030 Production History Match

Well-031

Figure 13-23: Scenario 5 – Well-031 Production History Match

Well-035

Figure 13-24: Scenario 5 – Well-035 Production History Match

Well-038

Figure 13-25: Scenario 5 – Well-038 Production History Match

Well-040

Figure 13-26: Scenario 5 – Well-040 Production History Match

Well-041

Figure 13-27: Scenario 5 – Well-041 Production History Match

Well-042

Figure 13-28: Scenario 5 – Well-042 Production History Match

Well-043

Figure 13-29: Scenario 5 – Well-043 Production History Match

Well-047

Figure 13-30: Scenario 5 – Well-047 Production History Match

Well-049

Figure 13-31: Scenario 5 – Well-049 Production History Match

Well-051

Figure 13-32: Scenario 5 – Well-051 Production History Match

Well-053

Figure 13-33: Scenario 5 – Well-053 Production History Match

Well-055

Figure 13-34: Scenario 5 – Well-055 Production History Match

Well-057

Figure 13-35: Scenario 5 – Well-057 Production History Match

13.2.3 Average History Match of Production

Figure 13-36: Scenario 5 – Well-001 Production History Match

Figure 13-37: Scenario 5 – Well-003 Production History Match

Well-004

Figure 13-38: Scenario 5 – Well-004 Production History Match

Well-005

Figure 13-39: Scenario 5 – Well-005 Production History Match

Well-006

Figure 13-40: Scenario 5 – Well-006 Production History Match

Well-008

Figure 13-41: Scenario 5 – Well-008 Production History Match

Well-011

Figure 13-42: Scenario 5 – Well-011 Production History Match

Well-012

Figure 13-43: Scenario 5 – Well-012 Production History Match

Well-014

Figure 13-44: Scenario 5 – Well-014 Production History Match

Well-017

Figure 13-45: Scenario 5 – Well-017 Production History Match

Well-026

Figure 13-46: Scenario 5 – Well-026 Production History Match

Well-028

Figure 13-47: Scenario 5 – Well-028 Production History Match

Well-029

Figure 13-48: Scenario 5 – Well-029 Production History Match

Well-032

Figure 13-49: Scenario 5 – Well-032 Production History Match

Well-033

Figure 13-50: Scenario 5 – Well-033 Production History Match

Well-034

Figure 13-51: Scenario 5 – Well-034 Production History Match

Well-036

Figure 13-52: Scenario 5 – Well-036 Production History Match

Well-037

Figure 13-53: Scenario 5 – Well-037 Production History Match

Well-039

Figure 13-54: Scenario 5 – Well-039 Production History Match

Well-044

Figure 13-55: Scenario 5 – Well-044 Production History Match

Well-045

Figure 13-56: Scenario 5 – Well-045 Production History Match

Well-048

Figure 13-57: Scenario 5 – Well-048 Production History Match

Well-050

Figure 13-58: Scenario 5 – Well-050 Production History Match

Well-052

Figure 13-59: Scenario 5 – Well-052 Production History Match

Well-054

Figure 13-60: Scenario 5 – Well-054 Production History Match

Well-056

Figure 13-61: Scenario 5 – Well-056 Production History Match

13.2.4 Poor History Match of Production

Figure 13-62: Scenario 5 – Well-016 Production History Match

13.2.5 Good Forecast Production

Figure 13-63: Scenario 5 – Well-002 Forecast Production

Figure 13-64: Scenario 5 – Well-010 Forecast Production

Well-015

Figure 13-65: Scenario 5 – Well-015 Forecast Production

Well-029

Figure 13-66: Scenario 5 – Well-029 Forecast Production

Well-031

Figure 13-67: Scenario 5 – Well-031 Forecast Production

Well-035

Figure 13-68: Scenario 5 – Well-035 Forecast Production

Well-042

Figure 13-69: Scenario 5 – Well-042 Forecast Production

Well-044

Figure 13-70: Scenario 5 – Well-044 Forecast Production

Well-047

Figure 13-71: Scenario 5 – Well-047 Forecast Production

Well-049

Figure 13-72: Scenario 5 – Well-049 Forecast Production

Well-051

Figure 13-73: Scenario 5 – Well-051 Forecast Production

13.2.6 Average Forecast Production

Figure 13-74: Scenario 5 – Well-013 Forecast Production

Figure 13-75: Scenario 5 – Well-017 Forecast Production

Well-019

Figure 13-76: Scenario 5 – Well-019 Forecast Production

Well-022

Figure 13-77: Scenario 5 – Well-022 Forecast Production

Well-023

Figure 13-78: Scenario 5 – Well-023 Forecast Production

Well-024

Figure 13-79: Scenario 5 – Well-024 Forecast Production

Well-027

Figure 13-80: Scenario 5 – Well-027 Forecast Production

Well-032

Figure 13-81: Scenario 5 – Well-032 Forecast Production

Well-034

Figure 13-82: Scenario 5 – Well-034 Forecast Production

Well-036

Figure 13-83: Scenario 5 – Well-036 Forecast Production

Well-038

Figure 13-84: Scenario 5 – Well-038 Forecast Production

Well-039

Figure 13-85: Scenario 5 – Well-039 Forecast Production

Well-040

Figure 13-86: Scenario 5 – Well-040 Forecast Production

Well-041

Figure 13-87: Scenario 5 – Well-041 Forecast Production

Well-043

Figure 13-88: Scenario 5 – Well-043 Forecast Production

Well-045

Figure 13-89: Scenario 5 – Well-045 Forecast Production

Well-050

Figure 13-90: Scenario 5 – Well-050 Forecast Production

Well-052

Figure 13-91: Scenario 5 – Well-052 Forecast Production

Well-055

Figure 13-92: Scenario 5 – Well-055 Forecast Production

13.2.7 Poor Forecast Production

Figure 13-93: Scenario 5 – Well-003 Forecast Production

Figure 13-94: Scenario 5 – Well-025 Forecast Production

Well-048

Figure 13-95: Scenario 5 – Well-048 Forecast Production

Well-053

Figure 13-96: Scenario 5 – Well-053 Forecast Production

Well-054

Figure 13-97: Scenario 5 – Well-054 Forecast Production

Well-056

Figure 13-98: Scenario 5 – Well-056 Forecast Production

Well-057

Figure 13-99: Scenario 5 – Well-057 Production History Match

13.3 Distribution Maps

Distribution maps are presented at different timesteps, including the beginning, middle, and end of the year.

Reservoir Pressure (psi) at 2014-01-31

Water Saturation (%) at 2014-01-31

Reservoir Pressure (psi) at 2014-06-30

Water Saturation (%) at 2014-06-30

Reservoir Pressure (psi) at 2014-12-31

Water Saturation (%) at 2014-12-31

Reservoir Pressure (psi) at 2015-06-30

Water Saturation (%) at 2015-06-30

Reservoir Pressure (psi) at 2015-12-31

Water Saturation (%) at 2015-12-31

Reservoir Pressure (psi) at 2016-06-30

Water Saturation (%) at 2016-06-30

Figure 13-100: Scenario 5 – Distribution Maps at Different Timesteps