INVESTIGATION OF DISPERSION AND ITS EFFECT ON THE SURFACTANT-POLYMER FLOODING PROCESS

A Thesis in
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by
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Abstract

Surfactant-polymer (SP) flooding holds significant promise for enhanced oil recovery, but the procedure for determining the best choice of chemical slug sizes does not consider reservoir mixing. Reservoir mixing at pattern scale can affect optimal slug sizes, but to date there is a lack of understanding of its impact. This thesis examines the impacts of mixing on SP flooding, and to show how grid-block sizes can be optimized through characterizing dispersion. Through these contributions SP flooding can become closer to becoming an economically viable production technique in the field.

In this thesis, design selection relies on showing incremental efficiency (STB oil/chemical mass) as a function of both SP slug and polymer buffer sizes. Thousands of UTCHEM simulations give tertiary recovery results across a range of tested designs and key input parameters. Important dimensionless groups are tested for their effects, as well as optimum salinity. Permeability upscaling into effective grid-blocks isolates the dispersion contribution from heterogeneity, and extrapolation to a block size of zero gives an estimate of physical mixing in the reservoir by matching concentration histories to the convection dispersion equation. Grid selection allows the largest block size to represent physical mixing. Optimized grid selection is shown to decrease computational time and uncertainty in project design. Economic analysis multiplies oil and chemical costs by the incremental efficiency and is optimized for profitability.

Mixing is shown to affect the strength and sweep of the SP slug, polymer buffer and salinity slug in the reservoir. Similar to miscible gas flooding’s minimum miscibility pressure and enrichment, surfactant’s critical micelle concentration (CMC) and concentration are greatly impacted, specifically when injection conditions are close to the CMC and optimum salinity. Unlike gas flooding, the effects of mixing on recovery depend on mixing of several components injected in different slugs and key reservoir parameters. Dependent on the process design, mixing can be beneficial or detrimental to efficiency; beneficial when increased sweep effects dominate, and detrimental when concentration effects dominate. The design of maximum process efficiency is described while varying key values, including heterogeneity and an effective chemical cost ratio on a per mass basis. Economic analysis indicates a larger slug design
than incremental analysis. An increasing trend is found between each component’s endpoint mobility ratio and measured dispersivity. A new parameter is defined in the fluid dispersivity factor, which characterizes the nature of each injected component’s impact to mixing, where the dispersivity of the component is divided by the dispersivity of a single-phase tracer. Favorable mobility ratios decrease mixing with a fluid dispersivity factor below unity, while adverse mobility ratios associated with components such as surfactant and gas in miscible gas flooding, increase the effective mixing with a dispersivity factor greater than unity.
# Table of Contents

List of Figures ................................................................. viii
List of Tables ................................................................. xiii
Acknowledgment ............................................................. xiv

Chapter 1: Introduction ......................................................... 1
  1.1 Problem Statement .................................................... 1
  1.2 Research Objectives .................................................. 2
  1.3 Organization of Thesis ................................................ 3

Chapter 2: Literature Review .................................................. 4
  2.1 Hydrodynamic Dispersion ............................................ 4
  2.2 Convective Spreading and Mixing ................................... 9
  2.3 Scale Dependence of Dispersion .................................... 10
  2.4 Heterogeneity Effects ................................................ 11
  2.5 Echo, Local and Transmission Mixing ............................ 12
  2.6 Numerical Dispersion ................................................ 13
    2.6.1 Implications of Using Grid-Blocks .............................. 14
    2.6.2 Derivation of Numerical Dispersion in Reservoir Simulation ........................................ 15
    2.6.3 Grid-Block Size and Numerical Dispersion ................. 19
  2.7 Mixing Effects on Miscible Displacement ....................... 20
  2.8 Polymer Flooding ..................................................... 20
  2.9 Surfactant Flooding .................................................. 21
    2.9.1 Surfactant Phase Behavior .................................... 22
    2.9.2 Interfacial Tension ............................................. 25
    2.9.3 Surfactant-Polymer Flooding ................................ 26
  2.10 Comparison of Miscible Flooding to Surfactant-Polymer Flooding ........................................ 26
    2.10.1 Similarities .................................................... 26
    2.10.2 Differences .................................................... 27
  2.11 Dimensionless Groups .............................................. 28
  2.12 Incremental Efficiency .............................................. 33

Chapter 3: Optimizing Grid Selection From Heterogeneous Dispersivity ........................................ 35
  3.1 Introduction ......................................................... 35
  3.2 Methodology ......................................................... 36
6.1 Summary ......................................................................................................................... 117
6.2 Conclusions..................................................................................................................... 118
6.3 Recommendations......................................................................................................... 120
Nomenclature ..................................................................................................................... 122
Equation Symbols ............................................................................................................. 123
References .......................................................................................................................... 126
Appendices ......................................................................................................................... 135
  Appendix A: Derivation of the Convection Dispersion Equation from Material Balance .......... 135
  Appendix B: Hand’s Model ................................................................................................. 138
  Appendix C: Sample UTCHEM Input Files ........................................................................ 140
  Appendix D: Convection Dispersion Curve Fitting .......................................................... 154
List of Figures

Figure 2.1 – A comparison between field measured dispersivity and echo dispersivity values for field-scale permeable media. Data from Arya et al. (1988). The plot includes lab-scale echo and transmission data from Hulin and Plona (1989). Source: Mahadevan et al. (2003). .............................................................................................................................................. 6

Figure 2.2 – Convective spreading of tracer through a tortuous permeable medium. No concentration gradients occur or change due to diffusion, only the successive subdivision of fluid flow into finer offshoots. Source: Bear (1972) ........................................................................................................................................ 10

Figure 2.3 – Echo, local and transmission dispersion in a 2-D cross section. Source: Garmeh et al. (2009). ........................................................................................................................................ 13

Figure 2.4 – Grid-block upscaling of local heterogeneities and flow channels. Fine details are replaced with a representative element of constant and uniform values. Source: Marques et al. (2011) ...................................................................................................................................... 14

Figure 2.5 – Single-point upstream weighting used to approximate fluid flow, and the superimposed finite-difference block-centered grid system. ..................................................................................................................... 16

Figure 2.6 – Ternary diagram of microemulsion phase behavior, showing one, two and three phases.....23

Figure 2.7 – Salinity scan of microemulsion phase behavior from Type II- to Type III to Type II+. Adapted from Sheng (2011) ........................................................................................................................................ 24

Figure 2.8 – Phase volume and IFT behavior for TRS 10-410/IBA system against n-Octane. Source: Glinsmann (1979) ........................................................................................................................................ 25

Figure 2.9 – Pareto plot showing the significance of key scaling groups in the estimation of dimensionless local dispersivities. Source Garmeh and Johns (2010). ........................................................................................................................................ 33

Figure 2.10 – Schematic of IOR from typical EOR response: (a) rate vs. time and (b) cumulative vs. time. Adapted from Lake et al. (2014). ........................................................................................................................................ 34

Figure 3.1 – Reservoir scale and grid-block scheme. ........................................................................................................................................ 36

Figure 3.2 – Base case simulation design permeability distribution. $\bar{k} = 200$ md, $V_{dp} = 0.40$, $\lambda_{x,p} = 0.50$, $\lambda_{y,p} = 0.031$. ........................................................................................................................................ 41

Figure 3.3 – Upscaling permeabilities using effective grid-blocks. (a.) An example permeability distribution with each block containing a unique value, then upon upscaling to the effective grid-block size outlined in gray (b.) the upscaled permeability in the fine-scale model ........................................................................................................ 42

Figure 3.4 – Upscaling and population of permeability values using effective grid-blocks. (a.) Original permeability distribution, (b.) upscaled permeability distribution using doubled effective grid-blocks, (c.) re-population of upscaled values into the fine-scale model................................................................................................................................. 44
Figure 3.5 – Fitting the convection dispersion equation to the simulated concentration profile for one grid-block

Figure 3.6 – Log-normal distribution of local dispersivity values in one column of the reservoir at $x_o = 1.0$

Figure 3.7 – $a_{Permeability}$ decreasing with grid-block size.

Figure 3.8 – Estimating $a_{Physical}$ from extrapolating $a_{Permeability}$ to an effective grid-block size of zero.

Figure 3.9 – Optimizing grid-block size by equating a physical level of dispersivity through permeability upscaling and numerical dispersion. The curve of $a_{Total}$ interests that of $a_{Physical}$ at a value of 0.0465.

Figure 3.10 – Upscaled permeability after matching physical dispersivity. (a.) Original permeability distribution and (b.) upscaled permeability distribution to match physical level of dispersion.

Figure 3.11 – Impact of vertical permeability ratio on calculated $a_{Permeability}$

Figure 3.12 – Impact of increased heterogeneity in $V_{DP}$ on calculated $a_{Permeability}$

Figure 3.13 – Effect of fine-scale grid-block size on calculating dispersivity. Shown from 32x16 grid-blocks (10 ft.) to 128x64 (2.5 ft.) and extrapolated to zero size using cubic spline extrapolation.

Figure 3.14 – Fit of convection dispersion equation to concentration profiles when there is significant crossflow of streamlines into one grid-block.

Figure 3.15 – $a_{Permeability}$ when upscaling only in the x-direction.

Figure 4.1 – Historical implementation of micellar-polymer flooding. Source Lindley (1986).

Figure 4.2 – Oil gravity range of oil that is most effective for EOR methods. Source: Taber et al. (1997).

Figure 4.3 – Illustration of a waterflood to determine the PVI when 95% watercut is reached.

Figure 4.4 – Heterogeneous permeability distribution. $\bar{k} = 200$ md, $V_{DP} = 0.80$, $\lambda_{x_p} = 0.50$, $\lambda_{z_p} = 0.03125$.

Figure 4.5 – Correlated permeability distribution. $\bar{k} = 200$ md, $V_{DP} = 0.40$, $\lambda_{x_p} = 5.00$, $\lambda_{z_p} = 0.03125$.

Figure 4.6 – Salinity injection gradient and optimal salinities used to test the effects of mixing.
Figure 4.7 – Concepts of MENP and MRNP for polymer flooding. The black line indicates the lowest possible incremental oil needed for a profitable project, which is for the limit of $n_p \to \infty$. Source: Adapted from Sieberer et al. (2017). 69

Figure 4.8 – Numerical simulation of surfactant-polymer flooding with different grid-block sizes of 5 ft. and 40 ft. 71

Figure 4.9 – Optimized grid selection results on surfactant polymer flooding. 72

Figure 5.1 – Oil recovery factor with various designs, of waterflood, polymer flood of 0.60 PV and 4.00 PV, and SP and polymer buffer designs of 0.30 PV-0.30 PV and 1.00 PV-3.00 PV. 75

Figure 5.2 – Recovery factor as a function of SP slug and polymer buffer sizes, % OOIP. 76

Figure 5.3 – Incremental recovery to waterflood as a function of design, STB. 76

Figure 5.4 – Pounds of effective chemical injected as function of design, using the base case chemical cost factors, where polymer costs $7/lb., surfactant costs $3.4/lb., and alcohol costs $1.4/lb. 77

Figure 5.5 – Incremental efficiency as a function of SP slug and polymer buffer sizes in pore volumes injected. Representative of the base case design. 78

Figure 5.6 – Polymer flood incremental efficiency with no SP injection. 79

Figure 5.7 – Surfactant-polymer flooding incremental efficiency with no trailing polymer buffer. 79

Figure 5.8 – Polymer incremental efficiency at small injection sizes. 80

Figure 5.9 – Effect of MI slug size on MI utilization. Source: Panda et al. (2009) 81

Figure 5.10 – Incremental efficiency as a function of SP flood design. Representative of the base case parameters and design, the black line indicates the zone of economic success. The blue O indicates the efficiency optimum design, and the red X denotes the economic optimum design. 82

Figure 5.11 – Incremental efficiency contour of $V_{op} = 0.40$, $S^* = 0.36$ meq/ml, $a_{Input} = 2.5$ ft., $\lambda_{sp} = 0.50$. Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 1.90 PV polymer buffer). 84

Figure 5.12 – Incremental efficiency contour of $V_{op} = 0.80$, $S^* = 0.36$ meq/ml, $a_{Input} = 0.0$ ft., $\lambda_{sp} = 0.50$. Incremental optimum (0.00 PV SP, 0.10 PV polymer buffer), economic optimum (0.00 PV SP, 0.40 PV polymer buffer). 85

Figure 5.13 – Incremental efficiency contour of $V_{op} = 0.40$, $S^* = 0.36$ meq/ml, $a_{Input} = 0.0$ ft., $\lambda_{sp} = 5.00$. Incremental optimum (0.10 PV SP, 0.60 PV polymer buffer), economic optimum (0.20 PV SP, 1.80 PV polymer buffer). 86
Figure 5.14 – Incremental efficiency contour of $V_{av} = 0.40$, $S^* = 0.24$ meq/ml, $\alpha_{input} = 0.0$ ft., $\lambda_{sp} = 0.50$. Incremental optimum (0.10 PV SP, 1.3 PV polymer buffer), economic optimum (0.10 PV SP, 2.5 PV polymer buffer). ................................................................. 87

Figure 5.15 – Surfactant and polymer concentrations (volume fraction, wt. %) in the reservoir at $t_p$ of 1.50 PVI, for the design of 0.10 PV SP, 0.50 PV polymer buffer. (a.) and (c.) denote surfactant concentration, (b.) and (d.) polymer concentration. (a.) and (b.) have no additional mixing while (c.) and (d.) have $\alpha_{input}$ = 2.50 ft. ................................................................................................................. 89

Figure 5.16 – Compositional analysis of surfactant and polymer across a very heterogeneous reservoir. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %). ..............90

Figure 5.17 – Compositional analysis of surfactant and polymer across a layered reservoir with increased permeability correlation length in the x-direction. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %). ................................................................................................................. 91

Figure 5.18 – Compositional analysis of surfactant and polymer concentration with a lowered optimal salinity of 0.24 meq/ml. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %). ................................................................................................................. 92

Figure 5.19 – Incremental efficiency and optimum designs with a changing oil price. (a.) $50/STB, (b.) $60/STB, (c.) $70/STB, (d.) $80/STB, (e.) $90/STB, (f.) $100/STB. ................................................................................................................. 94

Figure 5.20 – Economic design of SP and polymer buffer slug sizes for the base case design as a function of oil price. ................................................................................................................. 95

Figure 5.21 – Incremental efficiency and optimum designs with a changing effective polymer price. (a.) $3/lb. (b.) $7/lb., (c.) $11/lb., (d.) $15/lb., (e.) $19/lb., (f.) $37/lb. ................................................................................................................. 97

Figure 5.22 – Incremental efficiency and optimum designs with a changing surfactant price. (a.) $2/lb., (b.) $3/lb., (c.) $4/lb., (d.) $5/lb., (e.) $6/lb., (f.) $7/lb. ................................................................................................................. 99

Figure 5.23 – Comparing economic design of SP and polymer buffer slug sizes with mixing as a function of oil price. Sold lines indicate no additional mixing and dashed lines indicate $\alpha_{input}$ = 2.5 ft. .............101

Figure 5.24 – Effect of mixing near the CMC. (a.) Surfactant concentration (vol. fraction) with no added mixing and a CMC of 0.01, (b.) surfactant concentration with 2.5 ft. added dispersion. ......................... 102

Figure 5.25 – Salinity slug impacted by reservoir mixing. (a.) No added mixing, (b.) 2.5 ft. added dispersion. ................................................................................................................. 103

Figure 5.26 – Decrease optimal salinity, 0.21 meq/ml, resulting in small salinity gradient ............... 104

Figure 5.27 – Salinity slug with a low optimal salinity impacted by reservoir mixing. (a.) No added mixing, (b.) 2.5 ft. added dispersion. ................................................................................................................. 104
Figure 5.28 – Mixing effects shown as detrimental or as beneficial dependent on the size of injected slugs. Shown as a function of SP and polymer buffer slug sizes................................................................. 105

Figure 5.29 – Dispersivity Factor and endpoint mobility ratio................................................................. 107

Figure 5.30 – Comparison of dispersivity factor to results seen in other studies at adverse mobility ratios. Sources: Garmeh et al. (2009) and Connolly and Johns (2016). ................................................................. 108

Figure 5.31 – Incremental efficiency contour of $V_{dp} = 0.40, S^* = 0.36 \text{ meq/ml}, \alpha_{Input} = 0.0 \text{ ft.}, \lambda_{sD} = 0.50$ with adsorption introduced. Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 0.90 PV polymer buffer)........................................................................................ 112

Figure 5.32 – Incremental efficiency contour of $V_{dp} = 0.40, S^* = 0.36 \text{ meq/ml}, \alpha_{Input} = 2.5 \text{ ft.}, \lambda_{sD} = 0.50$ with adsorption introduced. Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 0.70 PV polymer buffer)........................................................................................ 113

Figure 5.33 – Salinity injection design with the SP slug injected at optimum salinity, followed by a polymer buffer below optimum............................................................................................................. 114

Figure 5.34 – Incremental efficiency contour of $V_{dp} = 0.40, S^* = 0.36 \text{ meq/ml}, \alpha_{Input} = 0.0 \text{ ft.}, \lambda_{sD} = 0.50$ with tapered salinity injection scheme. Incremental optimum (0.10 PV SP, 1.10 PV polymer buffer), economic optimum (0.10 PV SP, 3.00 PV polymer buffer). ........................................................................................ 115

Figure B.1 – Correspondence between (a.) ternary and (b.) Hand plot. Adapted from UTCHEM (2000). ........................................................................................................................................ 138
**List of Tables**

Table 3.1 – Key reservoir parameters held constant amongst all simulations. ............................................ 36

Table 3.2 – Courant number inputs for time-step selection. ................................................................................. 37

Table 3.3 – Component density inputs for UTCHEM simulation. .............................................................................. 38

Table 4.1 – Key injection parameters of each injection component. ................................................................. 59

Table 4.2 – Costs for an example polymer roll-out case. Source: Sieberer et al. (2017) ........................................... 67

Table 4.3 – Chemical costs for surfactant-polymer incremental efficiency and economic analysis. ............ 70

Table 5.1 – Summary of base case design properties and results. ................................................................. 83

Table 5.2 – Fluid dispersivity case studies. ........................................................................................................... 106

Table 5.3 – Adsorption input parameters ......................................................................................................... 111
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Chapter 1: Introduction

This chapter introduces the inspiration, aspirations and organization of this thesis. The significance of this research as well as objectives are also highlighted.

1.1 Problem Statement

Surfactant-polymer (SP) flooding is a promising chemical enhanced oil recovery technique that recovers oil by increasing the capillary number of trapped oil. The interfacial tension (IFT) is lowered not by creating a single phase as it is in miscible gas flooding, but by using chemicals to interact with the fluid interface. Dispersion is known to decrease fluid concentrations by spreading and lowers displacement efficiency in miscible displacements when compositions enter deeper into the multi-phase region. Dispersion also improves sweep efficiency and can increase recovery due to the same spreading process, when an increase in sweep efficiency outweighs the decrease in displacement efficiency. In chemical flooding, this spreading shows the same effects and can increase or decrease overall process efficiency with dispersion. Thus, dispersion is an important factor to understand in simulating a chemical enhanced oil recovery process like surfactant-polymer flooding. The current best practices for chemical flooding applications like SP flooding fail to acknowledge the importance of dispersion, which we hope to show is important to consider.

SP flooding has yet to become an economically proven recovery method in the field, largely due to its high chemical costs and complex nature. Enhanced oil recovery (EOR) techniques are important to research for the recovery potential they supply, and the fixed amount of worldwide oil reserves. Gaining a better understanding of these projects can push them toward full field-scale implementation and improve our recovery factors.

Many definitions of the optimal design can be given. Optimum definitions include the design that recovers the most oil, the design that makes the most money or the most efficient design. The second and
third definitions are of particular interest, for this knowledge is what is needed to prove the viability of SP flooding on a field scale.

Dispersion is an inevitable phenomenon affecting all fluids, and is present in all petroleum engineering applications. When building a reservoir simulation, it is necessary to match the level of mixing that occurs in the true field, to account for the physical process at play resulting from field heterogeneities. These simulations rely on using grid-blocks that describe sections of the reservoir large enough that we can model them. This simplification brings inherent error, as it homogenizes the small changes and heterogeneity we see in a physical reservoir. As we use these blocks, the dispersion generated in our model changes, as a function of the block size. By showing how the simulated dispersion changes with block size, we find the best sizes that match the same level of physical dispersion. A proposed methodology is needed to estimate the optimal grid system design.

1.2 Research Objectives

The main objectives of this research are to:

1. Investigate the impacts of reservoir mixing on the process of surfactant-polymer flooding.

2. Present insight on selecting an optimum injection design in slug sizes of both surfactant-polymer, and of the polymer buffer typically used.

3. Compare the mixing effects seen with surfactant-polymer flooding to those seen in miscible gas flooding.

4. Determine the dispersivity contribution of heterogeneous permeability distributions at incrementally larger block size and note the effects of upscaling.

5. Determine the largest grid-block size in the primary flow direction that will represent physical levels of reservoir mixing in simulations, with numerical dispersion and permeability driven dispersion.
1.3 Organization of Thesis

There are six chapters in this thesis. Chapter 2 covers an extensive literature review on dispersion in porous media, as well as the use of surfactants and polymers in chemical enhanced oil recovery floods. Important dimensionless groups and reservoir properties are discussed.

In Chapter 3 we present a new method of characterizing the contribution of dispersion from heterogeneous permeability distributions using the convection dispersion equation. Effective grid-blocks and upscaling are used to isolate numerical and permeability driven dispersion, and extrapolation of a physical level of reservoir mixing is done. Simulation grid-block selection is then optimized by this process.

In Chapter 4, we investigate the effects of reservoir mixing on surfactant-polymer floods. We present the key model and assumptions used to analyze levels of mixing, from heterogeneity caused fluid flow variations, to numerical dispersion and added mixing. An application of the grid-block optimization is applied to highlight the importance of mixing in simulating surfactant-polymer flooding.

In Chapter 5, we present the results of our simulations and discuss our findings. Each tested group and parameter is highlighted with the impacts and effects it has on the process and those due to mixing. We highlight the differences seen in this study of surfactant-polymer flooding and to previous literature on miscible displacement. Lastly, we investigate the dispersion associated with each component in an injected fluid.

Finally, in Chapter 6 we provide a summary of the research and contributions, present the highlighted conclusions and give further recommendations for future research.
Chapter 2: Literature Review

In this chapter we discuss a comprehensive review of dispersion and its mechanisms, as well the incorporation of mixing in numerical simulation. We also discuss the effects of mixing on both miscible gas flooding and surfactant-polymer flooding. Chemical enhanced oil recovery is introduced with the two chemicals of interest to this research, surfactant and polymer.

2.1 Hydrodynamic Dispersion

Mixing of fluids in a porous medium is governed by molecular diffusion and mechanical dispersion, or convective spreading. Molecular diffusion is the transport of mass in a single phase through concentration gradients. First proposed by Taylor (1953), this process is modeled by Fick’s Law (Fick 1855), describing diffusive flux as,

\[
J = -D_o \frac{\partial C}{\partial x}
\]  

(2.1)

Here the diffusive flux, \( J \), is equated with the diffusion coefficient, \( D_o \), and the mass concentration gradient, \( \frac{\partial C}{\partial x} \). This law shows that diffusion occurs due to a concentration gradient. Mixing can be increased in a porous medium by an increase in the surface area between these concentration gradients, caused by velocity variations within the reservoir. This additional mixing is referred to as dispersion.

Hydrodynamic dispersion is defined as “the macroscopic outcome of the actual movements of the individual tracer particles through the pores and the various physical and chemical phenomena that takes place within the pores” (Bear 1972). Six mechanisms of dispersion presented by Bear (1972) are:

a) External forces acting on the fluid.
b) The microscopic intricate geometry of the pore system.
c) Molecular diffusion caused by concentration gradients.
d) Variations in liquid properties, such as density and viscosity, that affect the flow pattern.
e) Changes in the tracer’s concentration due to chemical and physical processes within the liquid phase.

f) Interactions between the liquid and solid phases.

These mechanisms highlight the implication of flow through a porous medium, that during flow, mixing will be greater than what would occur strictly through diffusion. Velocity variations in the fluid increase the surface area available to diffusion (Greenkorn 1983). Hydrodynamic dispersion is the combined effect of molecular diffusion and mechanical dispersion (Pickens and Grisak 1981).

To represent hydrodynamic dispersion, following the work of Taylor (1953), Perkins and Johnston (1963) proposed the term $K_l$, the longitudinal dispersion coefficient. This can be represented by Equation 2.2 in a capillary tube,

$$K_l = D_0 + \frac{v^2 a^2}{48D_0}$$

(2.2)

where $K_l$ is the longitudinal dispersion coefficient, $v$ is the average velocity, and $a$ is the radius of the capillary. Further, in a bead pack,

$$\frac{K_l}{D_0} = \frac{1}{F\phi} + \frac{\sigma d_p}{D_0}$$

(2.3)

where $F$ is the formation electrical resistivity factor, $\phi$ is the fractional porosity, $\sigma$ is a measure of inhomogeneity of the pack, and $d_p$ is the average particle diameter. $K_l$ represents both dispersion and diffusion. Above an interstitial pore velocity near 3 cm/day velocity-dependent dispersion dominates the process of diffusion (Lake et al. 2014). As dispersion dominates, Equation 2.3 can be expressed as,

$$K_l \approx a_lv$$

(2.4)

where, $a_l$ represents the longitudinal dispersivity. Dispersivity has units of length, and for the local mixing-flow regime is a more fundamental measure of dispersion than $K_l$ (Lake et al. 2014). Dispersivity is used to represent the level of mixing in the reservoir as well as in our simulations, and better characterizes the
porous medium (Sheng 2011). Many studies have focused on measuring dispersivity from field data (Pickens and Grisak 1981; Arya et al. 1988) and Figure 2.1 shows dispersivity measurements at the field and lab scale.

Figure 2.1 – A comparison between field measured dispersivity and echo dispersivity values for field-scale permeable media. Data from Arya et al. (1988). The plot includes lab-scale echo and transmission data from Hulin and Plona (1989). Source: Mahadevan et al. (2003).

Longitudinal dispersivity reflects the mixing associated with flow in the primary flow direction. Mixing also occurs in the transverse direction, which is represented by \( \alpha_t \), the transverse dispersivity. The primary focus of most research has been on \( \alpha_t \) as opposed to \( \alpha_z \), but horizontal transverse dispersivity has been found to be approximately 10% of the longitudinal dispersivity (Gelhar 1997). Vertically, transverse dispersivity is dominated by diffusion, and is approximated at 1% of the longitudinal dispersivity (Klenk and Grathwohl 2002; Gelhar 1997). Adepoju (2013) focused on both longitudinal and transverse mixing, where spatial variances in velocity increased transverse dispersion.
In petroleum engineering the longitudinal dispersion coefficient is used in the one-dimensional convection dispersion equation (CDE). The CDE describes one-dimensional fluid flow through an isothermal, incompressible porous medium, with ideal mixing and no reactions. A derivation of this equation is found in Appendix A, resulting in,

$$\phi \frac{\partial C}{\partial t} + u \frac{\partial C}{\partial x} - \phi K_i \frac{\partial^2 C}{\partial x^2} = 0. \quad (2.5)$$

The following dimensionless parameters can be defined to write Equation 2.5 in dimensionless form:

$$x_D = \frac{x}{L} \quad (2.6 \text{ a.})$$

$$t_D = \int_0^t \frac{u}{\phi L} dt \quad (2.6 \text{ b.})$$

$$C_D = \frac{C - C_i}{C_i - C_j} \quad (2.6 \text{ c.})$$

Then by using the following chain rules:

$$\frac{\partial}{\partial x} = \frac{\partial}{\partial x_D} \frac{1}{\frac{\partial}{\partial x}} \frac{1}{L} \quad (2.6 \text{ d.})$$

$$\frac{\partial}{\partial t} = \frac{\partial}{\partial t_D} \frac{1}{\frac{\partial}{\partial t}} \frac{u}{\phi L} \quad (2.6 \text{ e.})$$

we arrive at the dimensionless CDE,

$$\frac{\partial C_D}{\partial t_D} + \frac{\partial C_D}{\partial x_D} - \phi K_i \frac{\partial^2 C_D}{\partial x_D^2} = 0. \quad (2.6)$$

Here $C_D$ is the dimensionless mass concentration, normalized between the initial and injection concentration, $t_D$ is the dimensionless time in pore volumes injected (PVI), $x_D$ is the dimensionless distance.
traveled, normalized between the injector and producer well, \( u \) is the velocity, and \( L \) is the dimensional length of the reservoir from injector to producer.

Another dimensionless parameter can be introduced as the Peclet number,

\[
N_{Pe} = \frac{uL}{\phi K_i}.
\]  

(2.7)

The Peclet number reflects the time it would take for an advective-based process to transport a component the length of the reservoir, divided by the time it would take a diffusive-based process. With this definition, a large Peclet number indicates a convective-dominated flow system, and a low Peclet number (less than unity) indicates a dispersive-mixing-dominated flow regime. At the core scale, typical Peclet numbers are approximately 1,000, while at the reservoir scale values are around 10 (Johns et al. 2002).

This definition of Peclet number results in the common dimensionless form of the CDE,

\[
\frac{\partial C_D}{\partial t_D} + \frac{\partial C_D}{\partial x_D} - \frac{1}{N_{Pe}} \frac{\partial^2 C_D}{\partial x_D^2} = 0.
\]  

(2.8)

This form of the CDE is useful to solve different problems, including when multiple phases are present, if the fractional flows and saturations are constant (Delshad 1981). Typical boundary conditions imposed on this equation are:

\[
C_D(x_D,0) = 0
\]  

(2.9 a)

\[
C_D(\infty,t_D) = 0
\]  

(2.9 b)

\[
C_D(0,t_D) = 0
\]  

(2.9 c)

The exact analytical solution, derived by Laplace transform, is (Marle 1981),
\[ C_D = \frac{1}{2} \text{erfc} \left( \frac{x_D - t_D}{2 \sqrt{t_D N_{Pe}}} \right) + e^{x_D N_{Pe}} \frac{1}{2} \text{erfc} \left( \frac{x_D + t_D}{2 \sqrt{t_D N_{Pe}}} \right). \] (2.10)

Under the conditions when \( N_{Pe} \) and \( x_D \) become large, the second term of Equation 2.10 becomes negligible, and the solution can be simplified and approximated in the form (Lake et al. 2014),

\[ C_D = \frac{1}{2} \text{erfc} \left( \frac{x_D - t_D}{2 \sqrt{t_D N_{Pe}}} \right). \] (2.11)

### 2.2 Convective Spreading and Mixing

In the reservoir, fluids move due to mechanical dispersion and molecular diffusion. These two mechanisms can be challenging to differentiate, as both result in a spreading of injected fluid and apparent weakening of concentration. Convective spreading is caused by flow through the tortuous paths of the medium, where the individual channels cause a continuous division of the tracer or fluid. This results in the addition of mass into finer offshoots (Bear 1972). This spreading is different from that of diffusion, for there is no change in fluid composition or concentration, only the subdivision of flow into smaller channels, as demonstrated in Figure 2.2. Sharp breakthrough curves at a point in the reservoir layer are found, showing that the level of mixing is small, when on a larger scale there seems to be greater mixing (Pickens and Grisak 1981). This process mimics the effects of dispersion, as this motion of fluid into different pore channels spreads the injected fluid with distance.
Figure 2.2 – Convective spreading of tracer through a tortuous permeable medium. No concentration gradients occur or change due to diffusion, only the successive subdivision of fluid flow into finer offshoots.

Source: Bear (1972)

Coupled with the process of convective spreading is the process of diffusion. True mixing occurs only through diffusion and is the focus of this study. When analyzing on a large scale with different flow channels, a large amount of ‘mixing’ will be estimated due to the convective spreading of a tracer across a wide sample of porous media. If the concentration is averaged across several of these layers, a significant overestimate of dispersivity will be made, that grows linearly with distance (Garmeh et al. 2009). This large overestimate is referred to as “apparent” mixing.

A characteristic that separates convective spreading and “true” dispersive mixing, is the implications of reversibility and reversal of flow. Convective spreading is reversible, while dispersive mixing is irreversible and will cause the same effects no matter the flow direction.

2.3 Scale Dependence of Dispersion

Dispersion has been characterized as a scale dependent phenomenon by many authors (Pickens and Grisak 1981; Arya et al. 1988; Mahadevan et al. 2003; Coats et al. 2009; Garmeh et al. 2009). This trend can be realized by analysis of Figure 2.1, in that the scale of the measurement influences the estimation of
dispersivity. One driving force for this scale dependence comes from the convective spreading due to channeling. With scale there is greater opportunity for heterogeneities to perturb fluid velocities, increasing the surface area available to concentration gradients and diffusion, while also decreasing the characteristic length for equilibrium.

A linear trend of dispersivity with measurement length is often seen, but this is due to apparent mixing. Attempts directly correlating longitudinal dispersivity to length scale fail to show quality trends (Arya et al. 1988; Sheng, 2011). Time also has an impact on observed mixing, as mixing increases with time.

As fluids travel deeper into the reservoir, measured dispersivity values reach an asymptotic value. This agrees with the prediction of stochastic modeling (Gelhar and Axness 1983). This larger-scale dispersion measurement is treated as a function of time until these asymptotic values are reached (Pickens and Grisak, 1981). Thus, as the length traveled in the porous medium increases, the dispersivity will increase monotonically to a point until additional distance has a minimal effect. This is observed under favorable flow conditions, but at high mobility ratios a decrease in dispersivity at large distances can be seen (Connolly and Johns 2016). This deviation from the believed monotonic nature with scale is accentuated by a decrease in dispersivity with an increase in the layering of permeability values, and with increasing mobility ratio.

2.4 Heterogeneity Effects

Because reservoir mixing is heavily influenced by the surface area between concentration gradients and the channeling of fluid into different streams, heterogeneity has a significant influence on dispersion. Large values of heterogeneity have been shown to produce large values of dispersivity (Arya et al. 1988; Garmeh et al. 2009; Connolly and Johns 2016). Equation 2.3 relates the longitudinal dispersion coefficient in bead packs directly to an inhomogeneity factor. In a heterogeneous permeable medium, these differences in flow properties result in fluid flow perturbations, increasing the surface area available to diffusion.
Reservoir heterogeneity can be seen on both the microscopic and macroscopic scale. Dispersivity is an effect of fluid flow along streamlines, but streamline velocities are dependent on the macroscopic heterogeneity. Thus, dispersivity at the field scale is more dependent on the macroscopic than microscopic properties of heterogeneity (Pickens and Grisak 1981).

The quantification of reservoir heterogeneity on the macroscopic scale is related to permeability variations. Indications of this heterogeneity come in the variance relation of the distribution compared to one representative value, and of the nature of which these values are distributed across the reservoir. With an increase in the variance, the amount of mixing is shown to increase (Garmeh et al. 2009; Connolly and Johns 2016). As the reservoir becomes more layered and correlated horizontally, the amount of mixing decreases (Garmeh et al. 2009; Connolly and Johns 2016). Adepoju (2013) showed that transverse dispersion remains constant across a correlated medium, and continues to increase with heterogeneity unlike longitudinal dispersion.

2.5 Echo, Local and Transmission Mixing

When estimating dispersivity and mixing, the measurement methodology has a large impact on the results. There are three different types of dispersion that can be encountered, echo, local and transmission mixing (Mahadevan et al. 2003). Figure 2.3 demonstrates these measurement types. Echo dispersivity is the level of mixing estimated by injecting a tracer and reversing flow to produce the injected tracer. This method relies on the irreversibility of molecular diffusion, and the reversibility of convective spreading. Echo dispersivity is a constant value with length, and is caused by pore scale heterogeneity of the reservoir (Mahadevan et al. 2003). In a homogeneous reservoir, echo dispersivity reflects the longitudinal dispersivity (Garmeh et al. 2009).
Local mixing is the primary focus of this study and represents the level of dispersion seen at one specific point, or grid-block, in the reservoir. At the grid-block scale, the level of dispersivity is not affected as much by convective spreading and flow perturbations, but only by the small scale mixing due to diffusion. Local mixing is only truly measurable at a point, and owing to the current practice of finite sized elements used to represent the medium, is often overestimated through improper simulation.

Transmission mixing, or ‘cup mixing’ (Connolly and Johns 2016) is the mixing associated with a reservoir cross-section or well. This mixing overestimates the level of mixing due to the dominance of convective spreading across the domain and indicates “apparent” mixing.

2.6 Numerical Dispersion

For engineering applications, numerical simulation is an important tool to better understand to model reservoirs. Permeable porous mediums contain a level of detail and network of pores that cannot be computationally modeled. Thus, to simplify this complicated network on a larger scale, grid-blocks are introduced to represent the physical medium. In doing this, we are able to equate blocks to the average properties of the true region. This process of upscaling to large homogeneous blocks brings associated error and implications to mixing.
The error associated with the implementation of grid-blocks is often referred to as numerical dispersion. The term numerical dispersion owes to the smearing of concentration profiles, similar to what is seen in the physical effects of reservoir dispersion. This numerical dispersion term is often used to represent the physical level of mixing (Stalkup 1990; Haajizadeh et al. 1999; Garmeh and Johns 2010).

Section 2.6.1 introduces the effects of our assumptions in reservoir simulation relative to grid-blocks, and the error that intrinsically follows. In section 2.6.2, the most common and simplest form of numerical dispersion is derived to show the origins and important factors. Section 2.6.3 ties the two together indicating how to use the derivation of numerical dispersion from grid-block size to equate dispersion.

2.6.1 Implications of Using Grid-Blocks

The grid-block is used to assign average properties to a volume of the reservoir. These grid-blocks serve as a proxy for the complicated pore network associated with the medium to replace microscopic variations with averaged properties. This averaging homogenizes the reservoir, and the larger the blocks the greater the effective homogenization. Figure 2.4 shows the loss of flow complexities associated with upscaling.

![Figure 2.4](image)

Figure 2.4 – Grid-block upscaling of local heterogeneities and flow channels. Fine details are replaced with a representative element of constant and uniform values. Source: Marques et al. (2011)
Numerical dispersion is the term associated with the effective error of the grid-block assumption and is related to block size. The larger the block, the larger the error, or dispersion. This effect is driven by the smearing of concentration fronts across the entire surface area of the block, rather than to specific fluid flow patterns (Chaudhari 1971). This increased surface area available to diffusion greatly increases the relative dispersion of the model at large block sizes. As dispersion is also related to heterogeneity, the more homogeneous a model becomes, the lesser the amount of dispersion will take place. This two-sided effect of the grid-block, describes the dual nature of the assumption.

Connolly and Johns (2016) noted that “as grid-blocks increase in size, mixing associated with numerical dispersion increases, while mixing associated with permeability variations (and by-extension velocity variations) decreases owing to less contact between gas and oil”. This directly describes the dual nature of the grid-block assumption that we quantitatively describe in Chapter 3.

2.6.2 Derivation of Numerical Dispersion in Reservoir Simulation

Physical dispersion taking place in an oil and gas reservoir is often mimicked by numerical dispersion stemming from solving the CDE through finite-difference approximation with a single-point upstream weighting scheme. This dispersion is approximated by the leading error term from the approximation. Beginning with Equation 2.8, by ignoring the dispersion term, Equation 2.11 can be approximated to represent the convective flow process in the simulation,

\[
\frac{\partial C_b}{\partial t_d} + \frac{\partial C_b}{\partial x_d} = 0.
\]

Because of the nonlinearity of Equation 2.11, the finite-difference approximation method is introduced to solve the governing flow equation. This method superimposes a finite-difference grid system over the reservoir, allowing solutions to be found at discrete points, as shown in Figure 2.5.
This finite-difference system is used for a backward-difference spatially, with $x_D$. The Taylor series expansion of the spatial term is,

$$C_{i-1} = C_i - \Delta x_D \frac{\partial C_D}{\partial x_D} + \frac{\Delta x_D^2}{2} \frac{\partial^2 C_D}{\partial x_D^2} - \frac{\Delta x_D^3}{6} \frac{\partial^3 C_D}{\partial x_D^3} + H.O.T. \quad (2.12 \text{ a})$$

Here the dimensionless subscripts are dropped in order to display the differential descriptive terms, but the concentrations remain dimensionless. The term $H.O.T.$ is used to represent higher-order terms that result from the differencing scheme but are not explicitly written. Equation 2.12 a is then solved for the approximation of the differential term,

$$\frac{C_i - C_{i-1}}{\Delta x_D} = \frac{\partial C}{\partial x_D} - \frac{\Delta x_D}{2} \frac{\partial^2 C}{\partial x_D^2} - \frac{\Delta x_D^2}{6} \frac{\partial^3 C}{\partial x_D^3} - H.O.T. \quad (2.12 \text{ b})$$

Here $C_i$ represents the concentration at location $i$. This approximation is used to replace the partial differential term with respect to dimensionless distance. Similarly, a forward-difference is done with respect to $t_D$,

$$C^{n+1} = C^n + \Delta t_D \frac{\partial C_D}{\partial t_D} + \frac{\Delta t_D^2}{2} \frac{\partial^2 C_D}{\partial t_D^2} + \frac{\Delta t_D^3}{6} \frac{\partial^3 C_D}{\partial t_D^3} + H.O.T. \quad (2.13 \text{ a})$$

This is then solved for the approximation of the differential term,

$$\frac{C^{n+1} - C^n}{\Delta t_D} = \frac{\partial C}{\partial t_D} + \frac{\Delta t_D}{2} \frac{\partial^2 C}{\partial t_D^2} + \frac{\Delta t_D^2}{6} \frac{\partial^3 C}{\partial t_D^3} + H.O.T. \quad (2.13 \text{ b})$$
Here \( C^n \) represents the concentration at time \( n \). Equation 2.13 b is used to replace the partial differential term with respect to dimensionless time. The approximations of the two differential terms are then substituted back into the advection equation (2.11) to obtain Equation 214,

\[
\frac{\partial C_D}{\partial t_D} + \frac{\Delta t_D}{2} \frac{\partial^2 C_D}{\partial t_D^2} + \frac{\Delta t_D^2}{6} \frac{\partial^3 C_D}{\partial t_D^3} + \ldots H.O.T. + \frac{\partial C_D}{\partial x_D} - \frac{\Delta x_D}{2} \frac{\partial^2 C_D}{\partial x_D^2} + \frac{\Delta x_D^2}{6} \frac{\partial^3 C_D}{\partial x_D^3} - \ldots H.O.T. = 0. \tag{2.14}
\]

This equation denotes the full finite-difference approximation of the advection equation using Taylor series expansion. By keeping only the second-order derivatives and ignoring the higher terms, we then differentiate with respect to both \( t_D \) and \( x_D \) separately. This results in the simplified second order derivatives of Equations 2.15 a and 2.15 b,

\[
\frac{\partial^2 C_D}{\partial t_D^2} + \frac{\partial^2 C_D}{\partial t_D \partial x_D} = 0 \tag{2.15 a}
\]

\[
\frac{\partial^2 C_D}{\partial x_D^2} + \frac{\partial^2 C_D}{\partial x_D \partial t_D} = 0 \tag{2.15 b}
\]

Because \( C_D \) is a state function, we can equate the second order derivatives.

\[
\frac{\partial^2 C}{\partial t_D \partial x_D} = \frac{\partial^2 C}{\partial x_D \partial t_D} \tag{2.16}
\]

This equality allows the subtraction of Equation 2.15 b. from Equation 2.15 a to result in the following approximation of the second-order differential terms.

\[
\frac{\partial^2 C}{\partial t_D^2} \approx \frac{\partial^2 C}{\partial x_D^2} \tag{2.17}
\]

Equation 2.11 can then be written in the following manner.

\[
\frac{\partial C_D}{\partial t_D} + \frac{\partial C_D}{\partial x_D} + \left[ \frac{\Delta t_D}{2} - \frac{\Delta x_D}{2} \right] \frac{\partial^2 C}{\partial x_D^2} = 0 \tag{2.18}
\]
This represents the finite-difference solution of the advection equation. By comparing Equation 2.18 to the common dimensionless form of the CDE, Equation 2.8, we obtain the following identity,

$$\left[ \frac{\Delta t_D}{2} - \frac{\Delta x_D}{2} \right] = -\frac{1}{N_{p_e}}. \quad (2.19)$$

Equation 2.19 shows that the leading error term from single-point finite-differencing is equivalent to the dispersion term of the CDE. This identity is used to solve for the $N_{p_e}$, by simplifying out a term of $\frac{\Delta x_D}{2}$,

$$\frac{1}{N_{p_e}} = \frac{\Delta x_D}{2} \left[ 1 - \frac{\Delta t_D}{\Delta x_D} \right]. \quad (2.20)$$

To ensure stability in our solutions a small time-step, $\Delta t_D$, is used, typically smaller than one-hundredth the size of the grid-block, $\Delta x_D$. Therefore as $\Delta x_D \gg \Delta t_D$ and $\Delta t_D \rightarrow 0$, 

$$\frac{1}{N_{p_e}} \approx \frac{\Delta x_D}{2}. \quad (2.21)$$

Equation 2.21 results in the following identity for $N_{p_e}$ when we define uniformly sized grid-blocks,

$$N_{p_e} = \frac{2}{\Delta x_D} = \frac{N_{Blocks}}{2}. \quad (2.22)$$

By dimensional analysis and Equations 2.4 and 2.7, the longitudinal dispersivity from the truncation error of numerical dispersion, $a_N$, can be directly related to the size of the grid-block, in Equation 2.23 (Lantz 1971),

$$a_l = \frac{\Delta x}{2} = a_N. \quad (2.23)$$

Several methods have been used to reduce numerical dispersion, including using advanced upstream-weighting, central-differencing, higher-order finite-difference schemes and total-variation
diminishing (TVD) (Liu et al. 1994). Each of these methods have been shown to reduce the truncation error, but the use of higher-order methods has been shown to produce oscillations (Chang 1990). This thesis focuses only on the effects of numerical dispersion from single-point upstream weighting.

2.6.3 Grid-Block Size and Numerical Dispersion

As shown by Equation 2.23, the level of numerical dispersion is directly dependent on the size of the grid-blocks used in the simulation. In numerical simulation, modeling of fine-grid systems can be extremely computationally demanding, increasing the cost and time demands of simulation. To counteract this effect upscaling is typically done to use larger blocks representative of the reservoir. As upscaling takes place, larger numerical dispersion is generated from these larger blocks, resulting in the overestimation of mixing in the reservoir (Stalkup 1990; Haajizadeh et al. 1999).

The dual natured grid-block assumption becomes important with upscaling, as the nature of numerical dispersion opposes that of homogenizing the reservoir. The level of mixing is decreased compared to fine-scale models, for the decreased heterogeneity decreases velocity anisotropy (Garmeh and Johns 2010). The goal of any simulation is to represent a physical process reflective of reservoir conditions, and for this to occur the simulated dispersion must match that physically seen in the reservoir. The ensuing relation is thus proposed for one-dimensional (Garmeh and Johns 2010),

\[ \alpha_{\text{tot, FineScale}} = \alpha_{\text{tot, Upscaled}}. \]  

Here \( \alpha_{\text{tot, FineScale}} \) is the total longitudinal dispersivity of the fine-scale model, and \( \alpha_{\text{tot, Upscaled}} \) is the total dispersivity of the upscaled model using larger grid-blocks. Equation 2.24 states that the optimum grid refinement occurs when the total dispersivity of the upscaled model reflects that of the fine scale, or physical level of the reservoir. The total dispersivity is given as the sum of numerical dispersion and the physical dispersion, assuming there is no input dispersivity,

\[ \alpha_{\text{Total}} = \alpha_N + \alpha_{\text{Reservoir}}. \]  

(2.25)
The longitudinal subscript is not shown here to emphasize the different dispersivity values, but all values refer to longitudinal dispersivity. In addition to the longitudinal dispersivity, under two-dimensional transport the transverse dispersivity ideally should be upscaled as well, with Equation 2.26,

\[ \alpha_{\text{total}} = \alpha_{\text{Reservoir}}. \]  

\( \alpha_{\text{total}} \) represents the total simulated dispersivity, and \( \alpha_{\text{Reservoir}} \) is the dispersion resulting from reservoir processes. Due to the computational time and cost associated with fine blocks, the optimum grid-block system is thus the largest system reflecting a physical level of total dispersivity.

### 2.7 Mixing Effects on Miscible Displacement

Miscible displacement uses high pressured gas flooding to achieve miscibility with the oil in place, while also swelling the oil and lowering its viscosity, allowing greater flow of oil. Miscibility is dependent on the phase behavior and compositions of the injected gas and resident oil. Dispersion reduces the strength of the injected fluid, and can cause a loss of miscibility, driving the composition route into the two-phase region, reducing the efficacy of the process (Baker 1977; Walsh and Orr 1990; Johns et al. 1994; Stalkup 1998; Solano et al. 2001; Garmeh et al. 2009). It has been shown that as mixing increases, the minimum miscibility enrichment (MME) shifts to larger values, requiring more injected enrichment to make up for the concentration losses due to mixing (Johns et al. 2002).

Dispersion also has been shown to increase recovery due to the spreading and dilution of injected fluid to reach a greater volume of oil (Kitanidis 1994). This additional contact area or sweep of the fluid causes a complicated relation of mixing on overall recovery, for mixing is detrimental to the local displacement mechanism but can assist the sweep of the fluid (Haajizadeh et al. 1999).

### 2.8 Polymer Flooding

Polymer flooding increases the viscosity of an injected solution by adding a water-soluble polymer. This polymer increases the viscosity and reduces the aqueous phase permeability (Lake et al. 2014). These effects lower the mobility of the injected phase, allowing greater sweep to occur, as compared to a basic
water flood, resulting in more oil to be contacted and ultimately produced. Polymers are made of long-chained carbon backbones and dissolve into the aqueous phase. The ultimate effect of polymers is mobility control, although other mechanisms like the reduction of residual oil saturation have been proposed (Huh and Pope 2008; Sheng 2011). The primary focus of polymers in this thesis is the increased mobility control and volumetric sweep, as we assume the residual saturation to water and polymer are identical.

Polymers have been used in three main ways to produce oil (Lake et al. 2014):

a. Near-well treatments to shut off thief zones.

b. Crosslinking agents used to plug high-conductivity zones in situ with the reaction of a metal cation.

c. To control mobility of the injected fluid through permeability reduction and a viscosity increase.

The majority of polymer usage has come in the third method, and this is the focus of this thesis.

There are two main types of polymers, synthetic polymers and biopolymers. The main examples of each of these are hydrolyzed polyacrylamide (HPAM) and xanthan gum respectively. Polymers are long molecular compounds that are often subject to degradation, chemically or physically. Polymers are sensitive to formation water hardness and salinity, as these can have adverse effects on the polymers, changing their viscosity and effectiveness. A relation of polymer viscosity with salinity was first described by Flory (1953) and in HPAM increased salinity shields the charged groups, causing the molecules to coil, reducing viscosity. Shear rate of the fluid also has an important effect and can cause shear-thinning or shear-thickening of the fluid, as well as physical degradation or breaking of the polymers at high shear rates. Temperature also plays a key role and can further degrade polymer molecules. Most polymer flooding cases in the field have used HPAM due to its low cost and relatively high temperature tolerance (Sheng 2011). Xanthan gum is used due to its lowered sensitivity to formation salinity.

2.9 Surfactant Flooding

Surfactant flooding lowers the interfacial tension and capillary forces keeping oil trapped in the reservoir. Surfactants are surface-active agents that target the interface between oil and water due to their
molecular structure and bridge the gap between the two fluids, reducing the interfacial tensions. Surfactants used in EOR are composed of a hydrophobic tail and a hydrophilic head, thus are amphiphilic (Sheng 2011). There are several methods to introduce surfactant into the reservoir, including surfactant flooding, surfactant-polymers (SP) flooding, combining the two chemicals into one injection fluid, and alkaline-surfactant-polymers (ASP) flooding, which generates surfactants in situ from a chemical reaction between an injected alkaline and the resident oil. Alkali reduces adsorption of the synthetic surfactant. This study focuses on the injection of surfactant as well as a cosurfactant (alcohol), combined with polymer to form one injection fluid.

There are four main types of surfactants, depending on the charge associated with their head group (Ottewill 1984). These four types are anionic, cationic, nonionic and amphoteric. Anionic surfactants have a negatively charged head group and are the most commonly used surfactant, as they have low adsorption to sandstones (Lake et al. 2014). Cationic surfactants reflect the opposite case with a positively charged head when dissolved in water. This causes high adsorption rates in sandstones but allows them to be used in carbonates (Sheng 2011). Nonionic surfactants are not charged in water, thus are less sensitive to charge distributions of the rock and to the composition of the aqueous solution. Amphoteric surfactants display both a negatively and positively charged head group that changes with the pH of the solution.

Surfactants are expensive chemicals that generate ultralow interfacial tensions to recover trapped oil. This interfacial tension decrease is achieved when the chemicals reach the interface and create a microemulsion phase near optimum conditions. Microemulsion phase behavior is dependent on many parameters, including temperature, pressure, oil composition and salinity (Khorsandi et al. 2017).

2.9.1 Surfactant Phase Behavior

Three pseudocomponents are typically used to represent the physical behavior of surfactant flooding. A brine, oil, and microemulsion pseudocomponent are introduced. The microemulsion defines a combination of surfactant, cosurfactant, oil and water, and contains stable micelles of oil, water or both.
Phase behavior is typically represented on ternary diagrams to show regions of one, two and three phases, as shown in Figure 2.6, and was first described by Winsor (1954).

![Ternary diagram of microemulsion phase behavior](image)

**Figure 2.6 – Ternary diagram of microemulsion phase behavior, showing one, two and three phases.**

Figure 2.6 denotes the phase behavior representative of a Winsor type III, for it contains a three-phase tie-triangle region (Lake et al. 2014). This type falls between two other extremes of type II- and type II+, where there are at most two phases in each and the (±) represents the slope of the tie-lines, connecting lines of similar compositions. The region below the three-phase triangle represents the critical micelle concentration (CMC), where the surfactant concentration is insufficient to form a microemulsion phase.

Salinity changes the microemulsion phase behavior and is the most common gradient used to optimize phase behavior in a porous medium. To ensure optimum conditions are reached, a salinity gradient is imposed within the reservoir upon injection. Scans can be done with several parameters like oil composition, temperature or pressure, but is shown in Figure 2.7 with effective salinity.
Figure 2.7 – Salinity scan of microemulsion phase behavior from type II- to type III to type II+. Adapted from Sheng (2011).

Figure 2.7 shows the phase behavior changing with increasing effective salinity. Type II- is a two-phase region with continuous oil and micelles containing brine phase. As salinity increases a three-phase zone appears, with two two-phase lobes and a three-phase tie triangle. As salinity continues to increase, the three-phase triangle is bounded by both two-phase lobes, as there is a continuous oil phase, continuous brine phase, and a three-phase zone containing oil and water microemulsions. Increasing salinity further, the phase behavior shifts until there is one two-phase lobe showing a continuous brine phase, and an oil phase containing micelles in type II+. The gray dashed lines represent tie lines in the two-phase regions.

There has been an extensive amount of research into various methods to characterize and model this phase behavior (Winsor 1954; Salager et al. 1979; Acosta et al. 2003; Khorsandi et al. 2017). The model used in this study and in UTCHEM (UTCHEM 2000) is Hands Model (Hand 1939), shown in Appendix B. Ideally, the impacts of mixing would be demonstrated with the HLD-NAC equation of state model, but this was not available at this time.
2.9.2 Interfacial Tension

Interfacial tension (IFT) is described by the imbalance of intramolecular forces when two or more phases are present. These forces are especially large for immiscible fluids like oil and water. This resultant force traps oil inside pores, making it inaccessible to primary or secondary recovery. Most early surfactant research focused on lowering the IFT, and Healy and Reed (1974) showed that incremental oil is recovered when the viscous forces can overcome the capillary forces through surfactant flooding. IFT has been shown to be correlated with phase behavior (Huh 1979), and the minimum IFT occurs when the invariant point, or top of the tie triangle is centered in the ternary diagram between the brine and oleic phases. As a shift occurs from type II- to type II+, the IFT reaches its minimum in the type III region shown as the center diagram of Figure 2.7. This has been shown experimentally, in Figure 2.8.

![Figure 2.8](image-url)

Figure 2.8 – Phase volume and IFT behavior for TRS 10-410/IBA system against n-Octane. Source: Glinsmann (1979)
In Figure 2.8, the IFT drops to its minimum at the optimum salinity, $S^*$, in this case around 0.6 wt.% NaCl (Glinsmann 1979). This optimum point, or point of lowest IFT, is the target of any surfactant flood, in order to minimize IFT and maximize mobilized oil. The optimum salinity thus is defined as the salinity required to reach the lowest IFT’s, at the given oil composition, temperature and pressure, for that specific concentration of surfactant and cosolvent.

### 2.9.3 Surfactant-Polymer Flooding

In chemical flooding, the purpose of polymer is to increase the amount of oil contacted, while surfactants free the trapped oil. They are often injected together in one chemical slug, which is termed surfactant-polymer flooding. Typically, the SP slug is followed by a polymer buffer, used to control mobility and drive the SP slug through the reservoir. A typical SP slug is 10 to 50% of the floodable pore volume, while the mobility buffer is 50 to 100% of the floodable pore volume (Lake et al. 2014). These designs and how they are impacted by mixing is a main focus of this thesis.

### 2.10 Comparison of Miscible Flooding to Surfactant-Polymer Flooding

One common EOR process that aims to produce trapped oil left behind in the reservoir is miscible gas or solvent flooding. Solvent flooding became the leading EOR method in the United States around 2002 (Lake et al. 2014). This process relies on injecting a phase, generally a supercritical fluid, which becomes miscible with the resident oil, allowing mass transfer from the denser oil to the high viscosity injected solvent. This allows the residual oil to decrease to a hypothetical value of zero, although practically these methods are only partially miscible (Lake et al. 2014). Any gas can be used, and at high enough pressure and temperature can become miscible with the resident oil, but due to the low critical pressure of carbon dioxide, ethane and methane, these are the most common components used.

#### 2.10.1 Similarities

The concept of miscible gas injection and surfactant-polymer flooding is similar, to inject a fluid into the reservoir that will interact with the remaining oil and decrease the capillary forces holding it in place. This capillary force reduction frees the oil that is trapped, allowing it to flow and be produced. Both
processes involve phase behavior that dominates the effectiveness of the flood, and a critical concentration of the injected chemical. These concentrations are the minimum miscibility enrichment (MME) and the critical micelle concentration (CMC). Due to the cost of the injected fluids, both processes rely on the use of injected slugs, where the primary chemical is injected in a small slug, followed by a cheaper chase fluid.

2.10.2 Differences

The differences between miscible gas flooding and SP flooding relate to how they reduce the capillary forces trapping oil. In solvent flooding the oil becomes miscible with the injected fluid, where mass transfer allows the oil components to transfer to the low-viscosity and mobile injected phase and be produced. Interactions of phase behavior and flow mechanisms drive the compositions to a critical point. In SP flooding a chemical is introduced to target the interface of oil and water, to reduce the interfacial tension of the two and allow the oleic phase to flow through the porous system more freely.

The complexity of SP flooding is shown by the different components that must be optimized, for it contains multiple chemicals that are affected differently, unlike in miscible gas flooding where the injected fluid is one composition that is assumed to be uniformly impacted by parameters like pressure, temperature and mixing. This results in one optimum design for miscible gas flooding, where there can be multiple optimum designs in the case of SP flooding. This includes not only surfactant and polymer, but the salinity slug as well, as salinity has a great impact on both chemicals, and we typically inject below reservoir salinity, creating a salinity slug that is susceptible to mixing.

The optimum design in miscible flooding lies above the minimum miscibility pressure (MMP), and any point above this pressure allows the miscible mass transfer. There are no detrimental effects of pressure above this MMP, only the associated cost and challenge of maintaining that high pressure in the reservoir. Comparable to the MMP is the CMC, both limits of concentration that must be exceeded for efficacy of the injection and in any optimum injection design. In this case it is detrimental to go much above the CMC, as at high enough surfactant concentrations we can go above the tie triangle and prevent the ultra-low IFT’s necessary for flow.
The relation of these two processes, and the differences between the two with respect to mixing, is one of the primary focuses of this study. Further, costs would increase similarly to the MMP, but SP fronts target an optimum, and unlike the MMP going above or below can be detrimental to recovery.

2.11 Dimensionless Groups

Several dimensionless groups are useful to understand this thesis. Dimensionless parameters allow a comparison of properties or processes across different applications, thus are a good practice of reference.

The first set of dimensionless groups used in this thesis relate to the recovery, displacement and sweep efficiencies of any arbitrary component, but are applied mostly to oil and gas displacement (Lake et al. 2014). Bounded by zero and unity, they represent key characteristics that depict oil recovery.

**Recovery efficiency,** $E_R$

$$E_R = \frac{\text{Volume of oil recovered}}{\text{Volume of oil originally in place}}$$  \hspace{1cm} (2.27)

**Displacement efficiency,** $E_D$

$$E_D = \frac{\text{Volume of oil recovered}}{\text{Volume of oil contacted}}$$  \hspace{1cm} (2.28)

**Volumetric sweep efficiency,** $E_V$

$$E_V = \frac{\text{Volume of oil contacted}}{\text{Volume of oil originally in place}}$$  \hspace{1cm} (2.29)

**Areal sweep efficiency,** $E_A$

$$E_A = \frac{\text{Area of oil contacted}}{\text{Total area}}$$  \hspace{1cm} (2.30)
Vertical sweep efficiency, $E_Z$

$$E_Z = \frac{\text{Cross-sectional area of oil contacted}}{\text{Total cross-sectional area}}$$

(2.31)

The above definitions result in the following identities,

$$E_R = E_A E_Z = E_A E_Z E_D .$$

(2.32)

These efficiencies are the primary focus of reservoir applications in petroleum engineering, in finding ways to increase total recovery efficiency $E_R$, by influencing one or more of the parameters of Equation 2.32 in a cost effective way.

The second set of dimensionless groups describe important ratios of forces in the reservoir that effect the fluids of interest. These numbers indicate the flow regime and indicate what forces and effects can be targeted with engineering design.

*Capillary number, $N_{vc}$*

$$N_{vc} = \frac{u \mu}{\sigma}$$

(2.33)

The simplest form of the capillary number, $N_{vc}$, relates the ratio of the viscous forces to the local capillary forces (Lake et al. 2014). High capillary numbers should yield low saturations of trapped phases.

*Gravity number, $N_G$*

$$N_G = \frac{g \rho \Delta P}{u \mu}$$

(2.34)

The gravity number relates the gravity forces to the viscous forces. High gravity numbers should yield low saturations of trapped phases.
Bond number, $N_B$

$$N_B = \frac{g \rho \Delta P}{\sigma}$$

(2.35)

The bond number describes the gravity forces related to the local capillary forces.

Trapping number, $N_T$

$$N_T = \frac{u \mu + g \rho \Delta P}{\sigma}$$

(2.36)

The trapping number, $N_T$, relates the viscous and gravity forces to the local capillary forces. These definitions give the following identity for one-dimensional flow,

$$N_T = N_{vc} + N_B = N_{vc} + N_G N_{wc}$$

(2.37)

The third set of dimensionless groups represents reservoir heterogeneity measures, of both the variance and the spatial distribution.

Dykstra-Parsons coefficient, $V_{dp}$

$$V_{dp} = \frac{\bar{k} - k_g}{\bar{k}}$$

(2.38)

The Dykstra-Parsons coefficient quantifies the variance of a permeability distribution of the reservoir (Dykstra and Parsons 1950). It relates the median permeability, $\bar{k}$, to the permeability one standard deviation below, $k_g$. Although the range of the parameter is from zero to unity, most reservoirs have a $V_{dp}$ between 0.40 and 0.90 (Garmeh and Johns 2010).
Dimensionless longitudinal correlation length, $\lambda_{l0}$, and Dimensionless transverse correlation length, $\lambda_{t0}$.

The dimensionless correlation ratios define how the permeability values relate to one another in that flow direction. A small correlation ratio indicates random permeability, and a large correlation length increases communication between values and layers. The grid-block size in the respective direction is important to account for in that using a correlation length smaller than the size of the block is unphysical. Below the block size changing the correlation length will have no impact. Both of these values are the dimensional correlation length normalized by the representative reservoir size. In general, in a Cartesian system $\lambda_{l0}$ is large while $\lambda_{t0}$ is small.

Courant Number, $C$

$$C = \frac{Q\Delta t}{\Delta x \Delta y \Delta z \phi}$$  (2.39)

The Courant number is a dimensionless measure of the amount of change occurring in one grid-block. This relates the maximum injection or production rate for each well-block, $Q$, to the current time step and grid-block dimensions (UTCHEM 2000).

Peclet number, $N_{pe}$

$$N_{pe} = \frac{vL}{D_0}$$  (2.40)

The Peclet number gives the ratio of the time for advective and diffusive transport between injector and producer wells. Large Peclet numbers indicate low levels of mixing in the reservoir.
Mobility ratio, \( M \)

\[
M = \frac{k_{\text{thj}}}{\mu_{\text{Inj}}} \cdot \frac{k_{\text{Disp}}}{\mu_{\text{Disp}}}
\]

(2.41)

The mobility ratio describes the viscous forces of the displacing fluid to the displaced fluid, represented here as the mobility of the injected phase divided by the mobility of the phase being displaced. Here \( k \) represents the relative permeability, and \( \mu \) the phase viscosity. The endpoint mobility ratio, \( M^0 \), represents the mobility ratio using the relative permeability endpoint values.

Effective aspect ratio, \( R_L \)

\[
R_L = \frac{L}{H} \sqrt{\frac{k_z}{k_x}}
\]

(2.42)

The aspect ratio relates the time it takes fluid to travel the length of the reservoir in the longitudinal direction compared to the time to travel the transverse length. Here \( L \) represents the length of the reservoir in the transverse direction, \( H \) the height of the reservoir, \( k_z \) the vertical permeability in the transverse direction, and \( k_x \) the permeability in the longitudinal or x-direction.

The sensitivity of these dimensionless groups to dispersion have been studied by many (Garmeh and Johns 2010). Figure 2.9 displays the relative sensitivity of seven dimensionless groups, with the larger the sensitivity, the larger the impact on dispersion.
2.12 Incremental Efficiency

Incremental oil recovered (IOR) is defined as the amount of oil recovered due to a new process that would not have been recovered under the previous recovery mechanisms. This is the added oil volume directly associated with the implementation of any technique used to enhance oil recovery, as shown in Figure 2.10.
Figure 2.10 – Schematic of IOR from typical EOR response: (a) rate vs. time and (b) cumulative vs. time.

Adapted from Lake et al. (2014).

To relate the IOR to what is required in the new process, the term incremental efficiency is introduced. In processes where any fluid is injected, this is defined by the additional oil produced, IOR, divided by the mass of injected component. In terms of surfactant-polymer flooding this can be described by the volume of oil per mass of surfactant, mass of polymer, or of an effective chemical mass that relates the two. This definition shows the process efficiency, in a return on investment, of volume of oil per mass of chemical injected. Clearly, economics will impact the efficiency actually achieved.
Chapter 3: Optimizing Grid Selection From Heterogeneous Dispersivity

This chapter presents a basic study on dispersion and its various contributors in reservoir simulation. A methodology of isolating the effective dispersion from different processes and effects is given and used to show the dispersion contribution from a heterogeneous permeability distribution. The approach uses numerical simulation with upscaling of effective grid-blocks to estimate the level of dispersion.

The results for one-dimension indicate that two effective grid-block sizes, only one being physical, allow an accurate level of dispersion in the simulation. The optimal design minimizes computational time and cost through the largest block sizes matching physical dispersion. Heterogeneous permeability dispersion declines rapidly with block size as numerical dispersion linearly increases.

3.1 Introduction

Numerical simulations give petroleum engineers the ability to learn about their reservoir and test various production methods through trial and error without the large time and cost of implementing these processes physically. These simulations provide excellent tools to estimate production and optimize project development. Simulations are only valuable when giving physical results, reflective of phenomena in the reservoir. To reduce the computational time and cost, upscaling is done to represent the reservoir through a series of larger grid-blocks, where large grid-blocks allow fast solving of the principal flow equations. This upscaling reduces the heterogeneities in the reservoir and increases the associated error through numerical dispersion. Section 2.6.1 discussed the dual nature of the grid-block assumption when in a heterogeneous system as grid-block size is increased, the dispersion measured due to heterogeneity decreases, and the numerical dispersion resulting from truncation error increases.

Single-point upstream weighting results in a linearly increasing function for numerical dispersion (Equation 2.23), but there is no relation to calculate the dispersion contributed from permeability distributions. Adepoju (2013) used a simple methodology of running numerical simulations and fitting the concentration histories to the convection dispersion equation, where after subtracting the known numerical dispersion the reservoir dispersivity was isolated. We expanded this methodology to isolate the dispersivity
from permeability and to iteratively upscale the reservoir to find the optimal grid-block design allowing a physical level of mixing to be simulated.

3.2 Methodology

We used the University of Texas Chemical Flooding Simulator (UTCHEM 2000) to build and simulate an example reservoir. A two-dimensional Cartesian model was used. This two-dimensional model reflects line-drive flow from one injection well to one producing well. The scale and other structural parameters are listed in Table 3.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length, width, height</td>
<td>320 ft., 32 ft., 32 ft.</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.20</td>
</tr>
<tr>
<td>Average permeability, x-direction</td>
<td>200 md</td>
</tr>
<tr>
<td>Vertical permeability ratio (z-direction)</td>
<td>0.10</td>
</tr>
<tr>
<td>Lateral permeability ratio (y-direction)</td>
<td>1.0</td>
</tr>
<tr>
<td>Initial water saturation</td>
<td>0.50</td>
</tr>
<tr>
<td>Initial reservoir pressure</td>
<td>1000 psi</td>
</tr>
<tr>
<td>Initial effective salinity</td>
<td>0.40 meq/ml</td>
</tr>
<tr>
<td>Initial divalent cation concentration</td>
<td>0.003 meq/ml</td>
</tr>
</tbody>
</table>

Table 3.1 – Key reservoir parameters held constant amongst all simulations.

A 320 ft. reservoir is used with grid-block dimensions of 5 ft. x 32 ft. x 1 ft. Figure 3.1 shows a schematic of the reservoir, with a 64 x 1 x 32 grid.

Figure 3.1 – Reservoir scale and grid-block scheme.
3.2.1 Model Assumptions

The assumptions and simplifications in any model are important to understand the results and limitations. This section depicts several key assumptions and processes not considered in this study. All inputs and included parameters can be found in Appendix C, as Appendix C gives example input files used in this thesis.

Well specification

In this study the injection well is constant rate, with a rate of 100 cubic feet per day. The producing well is pressure specified, with a constant bottomhole pressure of 100 psi.

Time-step

An automatic selection of time-step size is used based on the relative changes of the components (UTCHEM 2000). The Courant number is used, with the maximum and minimum Courant number used for each time input, as shown in Table 3.2. For this Chapter the Courant number is greatly reduced to allow very fine time-steps to be used for accurate output analysis.

<table>
<thead>
<tr>
<th>Process</th>
<th>Minimum Courant number</th>
<th>Maximum Courant number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracer for dispersivity study</td>
<td>0.0001</td>
<td>0.01</td>
</tr>
<tr>
<td>Waterflooding</td>
<td>0.001</td>
<td>0.5</td>
</tr>
<tr>
<td>Surfactant-polymer</td>
<td>0.001</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Gravity effects

Gravity effects are neglected in this study. Thus, the gravity number is zero, and has no impact on vertical sweep efficiency, $E_z$.

Adsorption

Adsorption is not considered in this methodology in studying dispersivity of permeability distributions.
Porosity and compaction

The reservoir has uniform porosity and no compaction.

Temperature

Isothermal, at a constant initial and reference temperature of \( 77^\circ F \).

Reservoir depth and dip

Horizontal reservoir with a constant depth of 1,000 ft.

Cation exchange

Cation exchange is ignored with all input parameters of cation exchange set to zero. The impact of this assumption to SP flooding is expanded upon in Chapter 4. The methodology of this chapter injects a tracer in the reservoir brine, so the lack of cation exchange is negligible due to the absence of any ion differences in reservoir fluids.

Density

The density of all phases and fluids is assumed to be constant throughout the simulation, independent of pressure, temperature or concentration and saturation. These densities are listed in Table 3.3.

<table>
<thead>
<tr>
<th>Component</th>
<th>Density (psi/ft.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>0.433</td>
</tr>
<tr>
<td>Oil</td>
<td>0.368</td>
</tr>
<tr>
<td>Oil in microemulsion</td>
<td>0.368</td>
</tr>
<tr>
<td>Surfactant</td>
<td>0.42</td>
</tr>
<tr>
<td>Alcohol</td>
<td>0.346</td>
</tr>
</tbody>
</table>

Biodegradation

Biodegradation reactions are not considered.
Gas

The presence of gas is not considered. We assume the reservoir pressure is above bubble point.

Permeability

A heterogeneous, anisotropic permeability matrix is input to the model in the primary flow, or x-direction. Vertical and tangential permeability in the y-direction are assumed to be functions of the x-direction permeability. The permeability in these directions is found by multiplying by the corresponding permeability ratio,

\[ k_z = \left( \frac{k_x}{k_y} \right) k_x. \]  

(3.1)

The permeability ratios were constant for all simulations, with \( \frac{k_y}{k_x} \) set to unity, and \( \frac{k_z}{k_x} \) to 0.10.

These assumptions allow the process to be simplified, and to focus on what was identified as the key parameters of this study.

A single-phase tracer is used and the dimensionless concentration of tracer plotted with time for each grid-block. The underlying assumption of this technique is that there are two main types of dispersion in our simulations, in the form of \( \alpha_N \) and \( \alpha_{\text{Permeability}} \). We use the CDE (Equation 2.5) to find the total dispersivity, \( \alpha_{\text{Total}} \), from our simulations and apply our assumption to Equation 2.25, to obtain Equation 3.1,

\[ \alpha_{\text{Total}} = \alpha_N + \alpha_{\text{Permeability}}. \]  

(3.2)

This gives the total simulated dispersion as a combination of numerical dispersion and dispersion resulting from permeability distributions. This assumption inherently equates \( \alpha_{\text{Permeability}} \) to \( \alpha_{\text{Reservoir}} \). Our simulations therefore rely on knowing \( \alpha_N \), and observing how \( \alpha_{\text{Permeability}} \) changes with increasing grid-
blocks. To begin this process, we need a permeability distribution, at the finest scale applicable to the project of interest.

### 3.2.2 Permeability Generation

To represent a heterogeneous field through a given permeability distribution, a permeability simulator in FFTSIM (Jennings et al. 2000) was used to generate the desired data. A detailed description of this simulator is given by Garmeh (2010), as a Fourier series is representative of an artificial field, and permeability values are stochastically determined from the input seed values and reservoir characteristics. The mean permeability, Dykstra-Parns coefficient, and correlation lengths in the x and z-directions are input. All simulations in this thesis are at a mean permeability of 200 md, but this is the only constant input to the generator. A resulting log-normally distributed permeability is output that adheres well to the specified variance and spatial relations. There are many realizations however that can achieve the same value for Dykstra-Parns coefficient and correlation lengths. Analyzing the output distribution independently for Dykstra-Parns coefficient shows that the error associated from the given seed values is typically within 3%. The post-processing program by Garmeh (2010) is used.

For the bulk of this thesis a base case design permeability distribution was created and used. The base case value for $V_{DP}$ is 0.4, a fairly homogeneous case of a realistic reservoir (Garmeh and Johns 2010). The dimensionless correlation lengths given were 0.50 and 0.031 for the x and z-directions respectively. This represents a dimensional correlation length of 160 ft. and 1 ft. This vertical correlation length is the same size as the block size. This base case permeability is shown in Figure 3.2.
In addition to the pilot-scale cases in Figure 3.1, a small-scale model was generated with the maximum number of grid-blocks allowed under the limitations of UTCHEM and requirements of FFTSIM. These are a maximum of 10,000 grid-blocks, and a requirement of a multiplier of two in each direction. With these two constraints, the maximum number of blocks is 8,192. This model uses 128 blocks in the x-direction and 64 in the z-direction. We call this the small-scale model for it focuses on a reservoir section of 32 ft. x 0.25 ft. x 16 ft.

3.2.3 Upscaling with Effective Grid-Blocks

The level of dispersion that arises from permeability variations will change dramatically as the block size is changed. To isolate the two sources of mixing, a simple process of incremental upscaling with effective grid-blocks and a single-phase tracer test is done, to find the largest blocks that can be used to represent the true level of physical mixing. An effective grid-block is the scale that permeability is upscaled to, while the upscaled effective grid-block can be input to cover multiple physical grid-blocks. This defines an effective grid-block, as the grid-block size that permeability is upscaled to, before the new permeability value is reassigned to a fine scale. Dependent on the upscaling size, several true grid-blocks act together with identical permeability values as one effective grid-block. To quantify dispersion in a simulation, it is
important to look at the mixing of each grid-block, for this more accurately represents true and local mixing, not transmission or cup mixing. For this, concentration histories are used to show the level at mixing in each block, which if done at an infinitesimally small block size would represent a single streamline traveling through a point. Due to the finite size of grid-blocks, this method will ultimately represent multiple streamlines and some transmission mixing to a degree but using small enough blocks will improve accuracy and allow a better fitting process. Given this, the process should always begin with as fine-scale a model as possible given accurate geological data.

We simulate our fine-scale model, fit the data and estimate our first value of $\alpha_{\text{Permeability}}$. To optimize the scale of blocks in the simulation a curve of $\alpha_{\text{Permeability}}$ with increasing block size is required. To obtain this plot we upscale the permeability distribution with the use of effective grid-blocks.

Figure 3.3 – Upscaling permeabilities using effective grid-blocks. (a.) An example permeability distribution with each block containing a unique value, then upon upscaling to the effective grid-block size outlined in gray (b.) the upscaled permeability in the fine-scale model.

Figure 3.3 shows the difference between an effective grid-block (outlined in gray) and of the actual scheme used (outlined in black). Permeability is upscaled using arithmetic averaging, then reassigned to the same fine grid as shown in Figure 3.4. The first step is to take the fine-scale permeability distribution and upscale it to a desired effective grid-block size. The second step is to assign this upscaled permeability distribution to the original fine-scale size. This process is done for larger and larger effective blocks until
there is one grid-block in the limiting \((z\) in this case) direction. A value of \(\alpha_{\text{Total}}\) is found for each effective block size, and the known \(\alpha_y\) of the fine model is subtracted from each case.

This proposed methodology allows any upscaling technique to be used to define the effective grid-blocks. Several upscaling techniques have been shown to improve simulation results in terms of maintaining the characteristics of the distribution (Holden and Nielsen 2000) and by compositional analysis (Li and Durlofsky 2016). As the upscaling technique was not a main focus of this study, the simple method of arithmetic averaging was used.
Figure 3.4 – Upscaling and population of permeability values using effective grid-blocks. (a.) Original permeability distribution, (b.) upscaled permeability distribution using doubled effective grid-blocks, (c.) re-population of upscaled values into the fine-scale model.

3.3 Fitting the Convection Dispersion Equation

For each permeability distribution, before or after upscaling, we estimate the levels of dispersion through matching the output concentration histories of each grid-block to the exact solution of the CDE, given by Equation 2.10. A method of minimizing the sum of the errors squared across 10 pore volumes injected is used, by iteratively changing two parameters, $N_{Pr}$ and $\Delta t_{D_{max}}$. This process is done using a Visual Basic for Applications (VBA) macro in Microsoft Excel, given in Appendix D.
The Peclet number is estimated so that we can solve for dimensionless dispersivity with Equation 3.3,

\[ \alpha_{\text{total}} = \frac{1}{N_{pr}} \] 

where \( \alpha_{\text{total}} \) is the measured value from the simulation, using the fine-scale grid-blocks. \( \Delta t_{\text{Pnts}} \) is used to align the curves, allowing a fair comparison of the relative error between concentration history and that predicted by the CDE. Because of the scale dependence of dispersion, a single distance traveled in the reservoir is selected to give each value of \( \alpha_{\text{total}} \). For this work we use a value of \( x_D \) of 1.0 for all cases, representing the location of the output well. This selects a vertical cross-section of interest. Each of these is then fit using the CDE, with an example of this fit shown in Figure 3.5.

![Figure 3.5 – Fitting the convection dispersion equation to the simulated concentration profile for one grid-block.](image)

The fit between the numerical simulation results and CDE is excellent as shown here, with each block given a unique dispersivity. These values are logarithmically averaged for each grid-block in the same column to calculate one average value, as done by Connolly and Johns (2016). Log-averaging is used due to the correlation of dispersion and permeability, and the given result of the permeability generator
FFTSIM that permeability follows a log-normal distribution. A relative frequency histogram of $\alpha_{\text{Total}}$ values at an $x_D$ of 1.0 is shown in Figure 3.6.

![Relative frequency histogram](image)

**Figure 3.6 – Log-normal distribution of local dispersivity values in one column of the reservoir at $x_D = 1.0$.**

Figure 3.6 confirms the log-normal distribution of dispersivity, justifying the averaging technique to estimate a single value of $\alpha_{\text{Total}}$ for each permeability distribution.

### 3.4 Results and Analysis

Once a value of $\alpha_{\text{Total}}$ is obtained, the known $\alpha_N$ of the fine-scale grid system is subtracted to isolate $\alpha_{\text{Permeability}}$. This process is repeated using larger effective grid-blocks, until the effective block size equals that of the limiting direction of the fine scale model, in this case 32 blocks. The values of $\alpha_{\text{Permeability}}$ are then plotted against their effective block size, showing the impact of upscaling on $\alpha_{\text{Permeability}}$. One case is shown in Figure 3.7.
The trend in Figure 3.7 agrees with the statements by Connolly and Johns (2016) that as block size is increased, the dispersion contribution from permeability variance decreases. There is a strong decline as the results rapidly approach zero, where a homogeneous model is reached, giving only numerical dispersion to $\alpha_{\text{Total}}$. This highlights the importance of using small enough grid-blocks to characterize the reservoir, as $\alpha_{\text{Permeability}}$ rapidly declines.

The purpose of obtaining this decline is to optimize the grid-block size used in reservoir simulation, to match the simulated dispersion to that seen physically in the reservoir. The physical level of dispersion, $\alpha_{\text{Physical}}$, is estimated by extrapolating the curve of $\alpha_{\text{Permeability}}$ to a block size of zero.

This hypothetical point would have no numerical dispersion, or truncation error, and $\alpha_{\text{Total}}$ would reflect $\alpha_{\text{Permeability}}$ exactly. This point is impossible to test directly, for every simulation is limited to finite sized grid-blocks. Cubic spline interpolation was used to extrapolate to an effective grid-block size of zero, as shown in Figure 3.8. Ideally, extremely fine grids would be used as well as detailed permeability distributions corresponding to our reservoir, with small $\Delta x_D$, would be used instead of extrapolating but the limitations previously described limit this methodology to extrapolation.
Figure 3.8 – Estimating $\alpha_{\text{physical}}$ from extrapolating $\alpha_{\text{permeability}}$ to an effective grid-block size of zero.

With the extrapolated point shown in gray on Figure 3.8, we then can begin constructing the plot necessary to optimize grid selection, and to show the four main values of $\alpha$ in this study. $\alpha_{\text{physical}}$ is extended from a block size of zero across the entire range of tested block sizes, as this is the physical value of the reservoir and independent of the grid-block size used in simulation. Next the $\alpha_{\text{permeability}}$ curve is added, based on effective grid-block sizes, as well as $\alpha_N$ using Equation 2.5, where $\alpha_N$ linearly increases with block size (Equation 2.23). We then use Equation 3.2 to calculate $\alpha_{\text{total}}$, by summing the values of $\alpha_N$ and $\alpha_{\text{permeability}}$, shown in Figure 3.9.
Figure 3.9 – Optimizing grid-block size by equating a physical level of dispersivity through permeability upscaling and numerical dispersion. The curve of $\alpha_{\text{Total}}$ interests that of $\alpha_{\text{Physical}}$ at a value of 0.0465.

By plotting $\alpha_{\text{Total}}$ we can find the grid-block size that should be used to match $\alpha_{\text{Physical}}$. There are two grid-block sizes that give a match to $\alpha_{\text{Permeability}}$. The first point is trivial and comes at the extrapolated block size of zero, something we can never truly reach in our simulations. The second point of intersections of these two curves is at a larger size, the optimum grid-block size. This second point of intersection is the largest block size allowing accurate characterization of dispersion in our simulation, indicated with the triangle in Figure 3.9. For this specific case and permeability distribution, the optimum block size is 0.047 $x_D$. With our reservoir length of 320 ft., this equates to 21 grid-blocks 14.9 ft. in length. The permeability distribution can then be upscaled to this size and is ready to use for simulation, as is done in Figure 3.10. Here the optimum block size is simplified for display purposes as 0.05, resulting in 20 grid-blocks 16 ft. in length.
A sensitivity analysis of two key parameters was done. This analysis used the fine-scale model and the pattern-scale model. Garmeh and Johns (2010) displayed several key factors in Figure 2.9, inspiring the key factors chosen here. First, due to the use of a single-phase tracer test, the relative permeabilities of the initial and injected fluid are constant and equal to 1.0. By maintaining a constant reservoir size for comparison, the shape and ratio of the length to height of the reservoir is held constant. Thus, when analyzing the aspect ratio, $R_L$, the key factor is the vertical permeability ratio. Most fields have a vertical permeability ratio around 0.1 (Lake et al. 2014). Here we tested this ratio at three values, with the impact to $\alpha_{\text{Permeability}}$ shown in Figure 3.11.
Figure 3.11 – Impact of vertical permeability ratio on calculated $\alpha_{\text{Permeability}}$.  

The vertical permeability ratio is shown to have an impact on $\alpha_{\text{Permeability}}$. No clear trend is identifiable from this sensitivity, other than that the values mirror each other with some overlap. The lowest values would be indicative of reservoir layers bounded with shale layers, where there would be negligible cross flow, while the highest values indicate vertical flow on the same magnitude as in the primary direction. The fine-scale model shows a direct correlation that as the vertical permeability ratio decreases greatly so does the dispersivity, which is not shown by the pattern-field scale.

The most influential parameter to dispersion proposed by Garmeh and Johns (2010) was the Dykstra-Parsons coefficient. Three values were tested, with a low, medium, and high level of heterogeneity, $V_{DP}$ of 0.40, 0.65 and 0.90 in Figure 3.12.
Figure 3.12 – Impact of increased heterogeneity in $V_{DP}$ on calculated $\alpha_{Permeability}$.

$\alpha_{Permeability}$ is very sensitive to $V_{DP}$ as was shown by Garmeh and Johns (2010). This increase would also increase $\alpha_{Physical}$, and give a larger optimum grid-block size. By comparing Figures 3.11 and 3.12, the range of values measured for the sensitivity with $V_{DP}$ are much larger than that seen in changing the vertical permeability ratio.

3.5 Model Limitations

The methodology presented in this chapter illustrates the effects of upscaling on dispersion but is limited by its assumptions and design. The estimation of local dispersivity is only accurate at a point, measuring a single streamline. This would represent a single point of no size, but any grid-block used in simulation will carry a finite size and error, and is therefore impacted by streamlines passing through it. This introduces some cup mixing into the results, indicative that it is not true local mixing being measured. The smaller the initial fine-scale model, the closer this method can come to measure true mixing. Three different sized fine-scale models for the same permeability distribution with a $V_{DP}$ of 0.40 are shown in Figure 3.13. An upscaled permeability distribution to have 32x1x16 effective grid-blocks is used to estimate dispersivity, before being assigned to smaller true grid-block sizes. Once a permeability distribution is given it cannot be upscaled further without changing the distribution.
Figure 3.13 – Effect of fine-scale grid-block size on calculating dispersivity. Shown from 32x16 grid-blocks (10 ft.) to 128x64 (2.5 ft.) and extrapolated to zero size using cubic spline extrapolation.

Figure 3.13 shows the value of $\alpha_{\text{permeability}}$ extrapolated to an initial grid-block size of zero, where true local mixing would be measured. Spline interpolation is used. This plot indicates there could be significant overestimation of $\alpha_{\text{permeability}}$ by using finite sized grid-blocks, even as small as 2.5 ft. in length. This intrinsic error originates from the flow of multiple streamlines into a single reservoir block, where dispersion is measured with concentration history. Figure 3.14 shows a block with multiple streamlines, indicated by the concentration curve.
When multiple streamlines cross into one grid-block, the error from the CDE fit is increased substantially. To improve the fit, very fine grid-block sizes should be used. In this study we were limited to 10,000 blocks by UTCHEM.

Other model limitations include the time-step size and the availability of output data. As Equation 2.20 shows, the time step used influences dispersion if it is allowed to become large. We assume that it is small enough to be ignored, but by using a maximum number of grid-blocks this time step must also be decreased substantially. We maintain a step size 100 times smaller than block size. The concentration history must also be output at fine intervals to allow proper fitting, and in this case every 0.005 PVI we update our concentration profiles.

This methodology used the one-dimensional solution to the CDE. Since we have a two-dimensional model we only measure $a_l$, and assume that $a_t$ is one tenth the longitudinal value. Future research could also focus on $a_t$ for upscaling.

The process upscaled in both the x and z directions. An effective grid-block grows by the same factor in each direction, but upscaling in the x-direction is a common method to maintain characterization.
of layers. By keeping a constant grid-block size in the z-direction, and upscaling only in the x-direction the curve of $\alpha_{\text{Permeability}}$ does not decline as it does when using the encompassing effective grid-blocks, but slowly decreases.

![Figure 3.15 – $\alpha_{\text{Permeability}}$ when upscaling only in the x-direction.](image)

The optimization methodology fails in this case for the shape of the $\alpha_{\text{Total}}$ curve does not show the dual natured effect and is monotonically increasing.

Determining a physical level of reservoir mixing has been attempted for many years by several studies (Arya et al. 1988; Stalkup 1990; Garmeh et al. (2009)). This method estimates physical dispersion by extrapolating the curve of $\alpha_{\text{Permeability}}$ with block size to zero. This assumes no effects other than the intrinsic permeability distribution and relies on the accuracy of this distribution into the model. This is very sensitive to the method of extrapolation. Spline interpolation was selected for use, as it uses a piecewise polynomial scheme relating the slopes of the previous points, and how these slopes change. This extrapolation resulted in better estimates than both cubic and linear interpolation methods. These two other methods result in noticeable underestimation of dispersivity as they use the final linear slope of the two finest points, while the extrapolation should reflect the decreasing nature of the curve.
3.6 Conclusions

This chapter presented a methodology of determining dispersivity from numerical simulation. The dispersivity contributed from two main factors were isolated and used to optimize grid-block design by matching simulated dispersion to physical values. A method of isolating permeability’s contributions to dispersion is shown by using the convection dispersion equation and effective grid-block upscaling. The results of this methodology and other factors are given, and the main conclusions of this chapter include:

1. Dispersion contributions from reservoir heterogeneity through permeability variations can be isolated from total dispersivity by subtracting numerical dispersion.
2. The dual nature of the grid-block assumption is observed using effective grid-blocks that have been upscaled in permeability but not in physical size.
3. A physical level of reservoir dispersion is extrapolated from the curve of permeability’s dispersivity contribution with block size, at a grid-block size of zero.
4. Total dispersivity can be plotted by adding numerical dispersion to a measured permeability dispersivity curve, allowing optimization of grid-block design where total dispersivity equates physical mixing.
5. Key factor analysis reveals the sensitivity of dispersion to heterogeneity and vertical permeability.
Chapter 4: Effect of Mixing on Surfactant-Polymer Floods

In this chapter we present the methodology used to examine the effects of mixing on surfactant-polymer floods. Simulation of SP flooding was done across different chemical injection designs and with various levels of dispersion. We used the University of Texas Chemical Flooding Simulator (UTCHEM 2000) to carry out over six thousand total simulations. These results allow analysis of the effects of mixing on recovery, chemical sweep, displacement efficiency and process efficiency.

Extensive research has been applied to the impacts of mixing on the process of miscible displacement (Walsh and Orr 1990; Johns et al. 1994; Stalkup 1998; Solano et al. 2001; Garmeh 2010), yet little work has been applied to the effects of mixing and dispersion on chemical flooding, such as for SP flooding (Wright et al. 1987; Clifford 1988; Rai 2008; Najafabadi and Chawathe 2016). From the work on miscible flooding, it is hypothesized that many of the same effects will hold true for chemical flooding. The goal of this chapter is to set up an extensive methodology for testing the effects of dispersion and to allow comparison of these effects to that seen in miscible displacement.

4.1 Introduction

Enhanced oil recovery (EOR) is defined as recovery by the injection of materials not normally present in petroleum reservoirs (Lake et al. 2014). This term is often associated with tertiary recovery, but the two are not always synonymous. The term tertiary recovery stems from the idea of a third phase of production, where the reservoir is subjected to new methods to improve oil recovery. Primary recovery is defined as the oil recovery by natural drive mechanisms, with secondary recovery a technique that improves reservoir pressure and mechanically displaces oil, often by waterflooding, and tertiary recovery is any process following secondary (Lake et al. 2014). In this work we associate the process of water flooding as a secondary technique, and the use of chemical flooding, either polymer or SP, to be tertiary recovery.

Using the above definitions, the common method of SP flooding is to use it as a tertiary EOR process, following the secondary recovery of a waterflood. Chemical injection was designed to immediately
follow a waterflood. Thus, the incremental oil recovered and the incremental efficiency of the chemical EOR is related to the recovery of an extended waterflood.

The injection scheme in all simulations followed the same general process seen historically in micellar-polymer or SP flooding, shown in Figure 4.1. An initial waterflood is followed by a non-continuous injection, or slug, with a fluid containing surfactant and polymer (SP). Next, a polymer buffer is injected to allow sweep of the SP slug and is followed by chase water to drive the injected chemicals and mobilized oil towards the production well. In all cases, 5.6 total pore volumes are injected. IOR is defined as the incremental cumulative oil to water flood, at 5.6 PVI.

![Figure 4.1 – Historical implementation of micellar-polymer flooding. Source Lindley (1986).](image)

SP flooding relies on two main chemicals to be injected into the reservoir. Surfactants are introduced to increase the capillary number and free trapped oil by lowering interfacial tension, and polymer is added to control mobility. This study does not depict the effect of mixing on surfactant or polymer selection, or the concentration of each. Xanthan gum is used as the polymer in all cases and is present in the SP slug as well as the polymer buffer, in equal concentrations of 600 ppm. The surfactant used is petroleum sulfonate, with 3 weight percent of the injected fluid, present only in the SP slug. Other notable
concentrations and injection parameters are listed in Table 4.1, including the cosolvent alcohol injected alongside surfactant with a concentration of 3 weight percent.

Table 4.1 – Key injection parameters of each injection component.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Waterflood</th>
<th>Surfactant-Polymer</th>
<th>Polymer Buffer</th>
<th>Chase Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slug size, pore volumes</td>
<td>1.00</td>
<td>0.00-1.00</td>
<td>0.00-3.00</td>
<td>0.60-4.60</td>
</tr>
<tr>
<td>Surfactant concentration, wt. %</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Polymer concentration, ppm</td>
<td>0</td>
<td>600</td>
<td>600</td>
<td>0</td>
</tr>
<tr>
<td>Alcohol concentration, wt. %</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Effective salinity, meq/ml</td>
<td>0.40</td>
<td>0.20</td>
<td>0.20</td>
<td>0.40</td>
</tr>
<tr>
<td>Divalent cation concentration, meq/ml</td>
<td>0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>0.003</td>
</tr>
</tbody>
</table>

SP flooding may not always be the best practice for increased production, and this depends on the specific reservoir conditions and the viscosity of the oil (Taber et al. 1997). The reservoir design used in this study is the same reservoir structure designed for Chapter 3, displayed by Figure 3.1 and described further by Table 3.1. The oil used in this study has a viscosity of 15 cp, and an API gravity of 35°. Using Figure 4.2 and the low initial pressure of the reservoir, this makes this an ideal candidate for SP flooding.

![Figure 4.2 – Oil gravity range of oil that is most effective for EOR methods. Source: Taber et al. (1997).](image-url)
4.2 Model Assumptions

Similar to Chapter 3, it is important to understand all model assumptions. This section depicts several key assumptions and processes not considered in this study that build off of the given assumptions stated in section 3.2.1.

Inaccessible pore volume

Inaccessible pore volume (IPV) is the porous space that the polymer (or surfactant) does not penetrate (Dawson and Lantz 1972). These values are taken to be constant, independent of shear rate, viscosity, velocity, or temperature. IPV is used to find the volume of the reservoir available to each chemical,

\[
\phi_{\text{Surfactant}} = \phi(1 - IPV_{\text{Surfactant}}) \tag{4.1}
\]

\[
\phi_{\text{Polymer}} = \phi(1 - IPV_{\text{Polymer}}). \tag{4.2}
\]

Here \( \phi_{\text{Surfactant}} \) and \( \phi_{\text{Polymer}} \) represent the porosity available to the surfactant and polymer respectively. \( IPV_{\text{Surfactant}} \) is set to 0.0, and \( IPV_{\text{Polymer}} \) to 0.20, as 20% of typical laboratory (Berea sandstone) cores are inaccessible to polymers (Trushenski et al. 1974).

Chemical recovery

Chemical recovery through production for the purposes of reuse is not considered. Thus, the fraction of chemical recovered of both surfactant and polymer is not considered.

Surfactant and polymer adsorption

Similarly to Chapter 3, adsorption is not considered. Adsorption is a key parameter of many chemical flooding studies and a large inhibiting factor when using surfactants, but is largely not considered in this study.
Cation exchange

Cation exchange in the reservoir can be detrimental to SP flooding, as it changes the ionic environment through the replacement of one ion on the rock surface with another from the injected fluid (Smith 1978). Anionic surfactant floods are particularly sensitive, and cation exchange can lead to increased surfactant adsorption and decreased displacement efficiency through inhibiting IFT reduction and optimum phase behavior (Smith 1978). By excluding cation exchange in this study, adsorption is further simplified and ignored and the ion environment is simplified allowing optimum surfactant behavior (Lake and Helfferich 1978).

These assumptions allow the process to be simplified, and to focus on what was identified as the key parameters of this mixing study. Chemical EOR and SP flooding are complicated processes with more effects than could be tested within the scope of this research, providing ample opportunity for future research.

4.3 Design Parameters

To test the effects of mixing, simulations are done across a wide range of designs. From these results, the incremental efficiency is plotted as a function of both the SP slug size and polymer buffer slug size. These plots indicate the efficiency of the process at each particular design, and by varying different inputs, the effect of each on the process can be displayed.

Section 4.3.1 introduces the main term used in analyzing the effects of mixing on SP flooding and describes its origins. In section 4.3.2 we discuss the generation and source for all permeability distributions used in this study as well as the difference between each distribution and display each of the key parameters that were tested to show the effects of dispersion.

4.3.1 Incremental Efficiency

Representative of a true tertiary recovery, all cases involve a matured waterflood before any further action. This waterflood uses reservoir brine to displace oil towards the production well. The waterflood
used here was designed to be used until the watercut at the production well reached 95%. Watercut is defined as the volume of water per total produced volume at the surface. The ending value of 95% is typical of many field case projects (Sheng 2011). To begin every simulation case, a simulation to the end of the project was done with only this original water flood. The watercut was plotted to find the time of 95%, as shown in Figure 4.3.

![Watercut Fraction vs. Pore Volumes Injected](image)

**Figure 4.3 – Illustration of a waterflood to determine the PVI when 95% watercut is reached.**

For all simulations, across each tested design including $V_{Dp}$, the waterflood reached 95% within 0.05 PVI of the base case design. This time of injection occurred at 0.95 PVI. Thus to standardize the procedure, chemical flooding began after 1.00 PVI of water was injected for all simulations.

For a fair comparison of recoveries of various designs, the same dimensionless time should be used. In all cases, 5.6 total pore volumes are injected. This time, defined by the rate specification of the injector, was approximately 10 years of injection. IOR here is taken as the incremental cumulative oil to water flood, at 5.6 PVI. This ignores the economic limit seen in Figure 2.10 and compares only the end volume of oil recovered at a specific time.

Incremental efficiency is the ratio of a volume recovered to a mass injected. Thus, with the incremental volume of oil found at 5.6 PVI, a mass of chemical injected is needed to define efficiency.
With three types of chemicals injected, a chemical cost ratio is needed to relate surfactant and alcohol mass to an effective polymer mass, which is referred to as mass of chemical. Practically, surfactant flooding would not be done without polymer. Polymer flooding however, has been shown as an economically viable stand-alone recovery process at a field scale (Sheng, 2011; Sieberer et al. 2017). Because of this, the total chemicals injected and the economic factors are related to polymer flooding alone. To relate the mass of surfactant and alcohol to that of polymer, the factor \( \beta \) was introduced, with \( \beta_s \) and \( \beta_a \) for each defined:

\[
\beta_s = \frac{\text{Surfactant cost / lb. surfactant}}{\text{Polymer cost / lb. polymer}}
\]  

\[
\beta_a = \frac{\text{Alcohol cost / lb. alcohol}}{\text{Polymer cost / lb. polymer}}
\]  

(4.3)  

(4.4)

To visualize the incremental efficiency of each design, and to compare the effects of mixing and different parameters, contour plots of incremental efficiency are constructed. These allow the trends and shape of the response surface of each case to be seen clearly. The point of maximum process efficiency is found. These plots serve as the basis for comparison of one case to the next when changing process parameters.

### 4.3.2 Tested Parameters for Impact of Mixing

The parameters selected for all simulations are presented here. With longitudinal dispersivity, the best measure of mixing occurring in the reservoir and simulation, the parameters of interest are those that should change the total dispersivity of the simulation. To begin, the input dispersivity, \( \alpha_{\text{input}} \), was increased. The grid-blocks used in these runs were 5 ft. in length, so the numerical dispersion as a result of the truncation error was 2.5 ft. \( \alpha_{\text{input}} \) was used to double this value, and 2.5 ft. was added to compare to the base case design.

The next parameter changed was the permeability distribution, as heterogeneity impacts mixing and can increase the total dispersion of a reservoir (Lake et al. 2014). The same permeability generator in FFTSIM (Jennings et al. 2000) was used to create permeability distributions with the desired distributive
properties, as described in Chapter 3.2.2. The two identified heterogeneity parameters were the measure of variance and the distribution of values, in $V_{dp}$ and $\lambda_{zp}$ and $\lambda_{zd}$. These parameters were changed in relation to the base case distribution, shown in Figure 3.2 in Chapter 3, where $V_{dp} = 0.40$, and $\lambda_{zp} = 0.50$, and $\lambda_{zd} = 0.03$.

From this base case permeability distribution, two measures of heterogeneity were increased. First a case with a $V_{dp}$ of 0.80 was run. Next, $\lambda_{zd}$ was increased to 5.0. This results in a correlation of permeability five-times the length of the reservoir, thus a strongly layered reservoir. $\lambda_{zd}$ was held constant for this case at 0.03. These distributions are shown below:

![Figure 4.4 – Heterogeneous permeability distribution.](image)

$k = 200$ md, $V_{dp} = 0.80$, $\lambda_{zp} = 0.50$, $\lambda_{zd} = 0.03125$. 

64
Next, the impact of salinity was investigated. This was done by keeping the same injection design across the base case and all simulations, but the optimum salinity, $S^*$, of the surfactant was altered. This is representative of a case where the chemical flood was designed for an optimal salinity that was falsely measured from the reservoir. The base case design had an optimal salinity of 0.36 meq/ml. This is defined by the midpoint of the upper and lower bound of effective salinity, $C_{SEU}$ and $C_{SEL}$. These indicate the upper and lower salinity limit for the Type III phase region when the alcohol component and calcium approach zero concentration (UTCHEM 2000). In the design of the base case, the upper and lower limits were 0.40 and 0.32 meq/ml respectively. This denotes an effective salinity range of 0.08 meq/ml, which was maintained across all simulations. One case of optimum salinity being reduced to 0.24 meq/ml was done so by lowering the limits to 0.28 and 0.20 meq/ml respectively. Figure 4.6 gives the described salinity injection scheme held constant amongst simulations, as well as the two optimum salinities used.
Figure 4.6 – Salinity injection gradient and optimal salinities used to test the effects of mixing.

An injection design was constructed to build a salinity gradient in the reservoir, the most effective way to optimize recovery in an SP flood (Pope et al. 1979; Hirasaki et al. 1983; Camilleri et al. 1987). With the formation brine at a higher effective salinity than the optimum, the chemical injection was designed below the optimum to ensure a salinity gradient crossing the optimum. The created gradient minimizes trapping behind the flood by ensuring the polymer buffer injection is at a salinity below optimum (Hirasaki et al. 1983). The ideal salinity gradient will result in an optimum salinity at the point of highest surfactant concentration (Nelson 1982). Often, the SP slug is injected at or near optimum while the trailing fluid will be injected below optimum (Rai 2008), but in this design both SP and polymer buffer slugs are injected below optimum.

4.4 Optimizing Design

In a practical application of simulating a SP flood, the incentive is to test the viability of the technique for field application. SP flooding has yet to become an economically proven method, likely because of high chemical costs, fluctuating oil prices and improper design and use of the technique. This study focuses on how the design of the floods can be improved through reservoir simulations accounting for the physical process of mixing. There are many ways that the optimum design can be selected, and the use of this term depends on the user’s definition.
4.4.1 Efficiency Optimum

The first definition of an optimum design used here is that giving a maximum incremental efficiency. This design maximizes the return on investment, in terms of volume of oil recovered divided by mass of chemical injected. On a contour diagram of incremental efficiency for various slug sizes of design, this represents the location of the peak, independent of economic viability. This definition of optimum design is, however, a function of the cost ratios, $\beta_s$ and $\beta_A$, used to equate an effective chemical mass in terms of pounds of total chemical injected. Changing these ratios changes the shape of the incremental efficiency contours, possibly resulting in a different maximum.

4.4.2 Economic Optimum

The second and likely more relevant definition of optimum design is in terms of profit from production. This definition relies heavily on several cost factors described here.

A detailed analysis of polymer flooding economics in the 8TH reservoir in Austria has been shown previously and here we follow the work of Sieberer et al. (2017). The economics of the SP flood are tied back to the economics of polymer flooding, since it is not typically practical to inject surfactant without polymer. The cost structure is split into two categories, the capital expenses (Capex) and the operational expenses (Opex). These various expenses are broken down in Table 4.2.

Table 4.2 – Costs for an example polymer roll-out case. Source: Sieberer et al. (2017)

<table>
<thead>
<tr>
<th>Capex, Summarized</th>
<th>Total</th>
<th>Phase 1</th>
<th>Phase 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capex facility and owners costs</td>
<td>$26,400,000</td>
<td>$22,687,500</td>
<td>$3,712,500</td>
</tr>
<tr>
<td>Capex/pattern (pipeline, well pads, pumps, workover injector)</td>
<td>$522,500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capex/new injector (drilling and completion only)</td>
<td>$880,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capex/new producer (drilling and completion, workover, surface)</td>
<td>$1,177,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opex, Summarized</td>
<td>Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opex: Plant operation and surveillance</td>
<td>$275,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opex: Polymer</td>
<td>$1.7/lb.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opex: Produced-water treatment</td>
<td>$330,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opex: Surveillance per pattern (tracers, injection/production)</td>
<td>$55,000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Here the costs of polymer flooding take into account drilling and completions costs of new wells, the installation of new surface facilities, as well as the costs of the chemicals themselves and other expenses.

The objective of this economic analysis is to calculate the necessary incremental oil from polymer flooding to result in a positive or zero net present value (NPV) of the project (Sieberer et al. 2017). This calculation is done using Equation 4.5 from Sieberer et al. (2017),

\[
NPV = I \cdot f_p \cdot c \cdot \frac{P}{E} - (\alpha + n_p \cdot \beta).
\]  

(4.5)

This equation relates the NPV to the incremental oil per pattern, \(I\), the oil price, \(P\), the number of patterns, \(n_p\), and the total discounted costs that are both independent and dependent on the number of patterns, \(\alpha\) and \(\beta\). The utility factor (UF) has often been used to denote the efficiency of a polymer flood (Yuan et al. 2010; Clemens et al. 2011; Laoroongroj et al. 2014). This UF is a simplified cost factor to the mass of polymer, showing the culmination of all costs and factors into a relation of the mass of polymer injected. Using the above equation and the costs given in Table 4.2, as well as a discount rate of 10% and an oil price of $75/STB, the UF necessary for the project to have a non-negative NPV is found to be 5.95 lb. of polymer/STB (Sieberer et al. 2017). By using the known costs, this equates to an incremental efficiency required for breakeven of an effective $12.6/lb. of polymer injected, including all associated costs and factors.

To incorporate the project scale, the parameters of the minimum number of economic patterns (MENP) and the minimum robust number of patterns (MRNP) are introduced (Sieberer et al. 2017). MENP gives the smallest number of patterns necessary for the project to become economic, or maintain a positive NPV. The MRNP is the smallest number of patterns for the project to be robust economically, where the project is not impacted greatly by the loss of one pattern. These apply the scale of the project to its overall feasibility. Small projects become extremely dependent on pattern dependent costs, as costs are not
sufficiently spread across the project. These small projects are also susceptible to the failure of one or two wells and patterns. This principle is displayed in Figure 4.7.

![Figure 4.7](image)

**Figure 4.7 – Concepts of MENP and MRNP for polymer flooding.** The black line indicates the lowest possible incremental oil needed for a profitable project, which is for the limit of \( n_p \rightarrow \infty \). Source: Adapted from Sieberer et al. (2017)

In this research we make a few key assumptions in terms of project economics to simplify the analysis. First we assume SP flooding begins after the majority of the costs have been sunk into the project. That is, we assume that the bulk of the wells, both injectors and producers, have already been drilled for the waterflood and polymer flood, thus these costs will not impact our economics as much as the case shown for the 8 TH reservoir. We assume that the number of these existing patterns is beyond the MENP to sufficiently divide surface facility costs, as well as over the MRNP. These assumptions prevent our economics from being driven by pattern dependent costs.

Due to the assumptions of decreased economic costs, the cumulative incremental cost per pound of chemical decreases from that found by Sieberer et al. (2017), and is assumed here to be an effective $7/lb. of polymer. This effective $7/lb. of polymer includes the remaining pattern specific and drilling costs, surface facility costs, water production and treatment, and all other associated costs. Also included in this number is the 10% discount rate. With the polymer incremental cost encompassing all associated costs, the
incremental costs for surfactant and alcohol reflect only the chemical costs. These costs, as well as their chemical cost ratios to polymer, are given in Table 4.3.

### Table 4.3 – Chemical costs for surfactant-polymer incremental efficiency and economic analysis.

<table>
<thead>
<tr>
<th>Chemical</th>
<th>Cost</th>
<th>Cost Factors</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polymer</td>
<td>$7/lb.</td>
<td>Chemical, Capex, Opex</td>
<td>-</td>
</tr>
<tr>
<td>Surfactant</td>
<td>$3.4/lb.</td>
<td>Chemical only</td>
<td>0.49</td>
</tr>
<tr>
<td>Alcohol</td>
<td>$1.4/lb.</td>
<td>Chemical only</td>
<td>0.20</td>
</tr>
</tbody>
</table>

The surfactant cost given in Table 4.3 describes the cost of active surfactant. This study assumes that all surfactant injected is active, thus all costs for the mass injected include only active surfactant. When purchasing surfactant there are different degrees of activity, and the total price of this mixture of active and inactive surfactant is given by Adibhatla and Mohanty (2008) as $1.4/lb. The cost assumed in this study is increased due to the assumption of purely active material with no sacrificial surfactant injected.

The associated costs are a function of location and will be different for every field. These costs and assumptions are meant to show a single example case, and to be used as a tool for analyzing the effects of mixing on the process of SP flooding. The economic breakeven point with these costs now comes at a UF of 10.7 lb. of chemical/STB incremental oil, or an incremental efficiency requirement of 0.0933 STB/lb. chemical.

In plotting the incremental efficiency as a function of slug size, it is useful to subtract the economic limit of 0.0933 STB/lb. chemical to see where the project will make or lose money. After subtraction, any positive value represents an incremental profit, while negative values represent an incremental loss.

A zone of economic success can be found by denoting the breakeven point on the contour plot. After subtraction of the economic limit this zone is given as a contour of zero. This line indicates the designs that result in zero profit, or an equal return in value of oil for the chemicals injected as well as associated costs. The economic optimum point must be along this line, for this optimum will maximize total profit by extending the project duration to maximize the volume of oil recovered while still generating profit. This
point is found by choosing the design resulting in the maximum oil recovery, inside the zone of economic feasibility.

4.5 Grid-Block Optimization Application to Surfactant-Polymer Flooding

A simplified analysis of the effects of mixing on SP flooding was designed to highlight the applications and impact of optimizing our grid-blocks for simulation through the methodology given in Chapter 3. The results of Chapter 3 show that $\alpha_{\text{permeability}}$ can be isolated and plotted with upcaled grid-block size, and the grid selection of a model can be optimized for dispersion. This methodology was applied to one example case study, with SP flooding. To see the importance of optimizing our grid-block design, two example cases were done, seeking the incremental optimum design of the SP slug, as was done by Galimberti (2017). No polymer buffer was used, to give a single curve of incremental efficiency rather than requiring a contour diagram. Each case was run using different grid-block sizes, of 5 ft. and 40 ft., to see how this impacted the optimal design for greatest efficiency. The large simplifications here are the absence of any polymer buffer, and the use of only one optimization method, in incremental efficiency, rather than including the economic optimum. The shift shown in Figure 4.8 would clearly alter the economic optimum design as well.

![Numerical simulation of surfactant-polymer flooding with different grid-block sizes of 5 ft. and 40 ft.](image)

*Figure 4.8 – Numerical simulation of surfactant-polymer flooding with different grid-block sizes of 5 ft. and 40 ft.*
Figure 4.8 shows how upscaling can affect our results when optimizing SP slug size. The fine case outperforms the coarse case, as the numerical dispersion is greatly reduced and surfactant concentrations are not smeared in the simulation. The optimal SP slug sizes for the 5 ft. and 40 ft. block cases are 0.2 PV and 0.45 PV, a difference of $140,000 in terms of chemical costs ($111,000 versus $251,000). This window shows why it is necessary to optimize block design, and to select a block size reflective of the physical processes.

The grid optimization methodology was followed, with the optimal grid-block design found in Figure 3.2 of 16 ft. This permeability distribution is shown in Figure 3.10. We can then be confident that this case reflects the physical level of dispersion in the reservoir, and the optimization of SP slug size is shown in Figure 4.9.

![Figure 4.9](image-url)  
**Figure 4.9 – Optimized grid selection results on surfactant polymer flooding.**

The optimum SP slug for the refined scale is 0.30 PV, with an associated chemical cost of $167,500. This is $83,000 less than the 40 ft. case, showing how we can remove uncertainty from our simulations through the use of this methodology. This can be applied to any numerical simulation that uses the grid-block simplification.

This simple case of an application to SP flooding shows the potential importance of mixing and grid-block scale of our simulations to SP flooding. With the importance shown on a simplified case with
only an SP slug, the remainder of this study focuses on highlighting the effects of mixing on both optimum designs, as functions of both SP and polymer buffer slug size. Ideally further simulations of chemical flooding should operate at the optimum grid size found through matching physical dispersion, but a finer model is used to greater highlight the differences of mixing.

4.6 Conclusions

This chapter described the methodology and simulation design to show the effects of mixing on surfactant-polymer flooding. The structure and key parameters of the model are given as well as the key assumptions made in the simulations. The main conclusions of this chapter include:

1. UTCHEM is used to simulate a line-drive chemical flood following a waterflood when watercut reaches 95 percent at the producing well. A SP slug is followed by a polymer drive and again by chase water until 10 years of injection, or 5.6 total pore volumes injected.
2. Chemical concentrations and salinities of injection slugs are held constant for all simulations, as well as the same basic assumptions and simplifications as included in the base case design.
3. The main properties tested for their mixing effects are added dispersivity, the Dykstra-Parsons coefficient, the permeability correlation lengths and the optimal salinity of the surfactant.
4. Two optimum designs are noted; the incremental efficiency maximum and the economic optimum, which maximizes oil produced under profitable conditions.
5. The economics of the project are included in the incremental polymer cost per pound, giving an economic limit of 0.0933 STB/lb. chemical necessary for profit for the examined case.
6. Application of optimizing grid-block sizes to match physical dispersivity highlights the importance of mixing in SP flooding, greatly changing the optimal design. This application reduced uncertainty of the model, chemical costs and computational time.
Chapter 5: Surfactant-Polymer Mixing Study Results

In this chapter we examine the effects of mixing on surfactant-polymer flooding. A comparison to previous research of gas and polymer flooding is given.

5.1 Introduction

A base case design was tested for incremental efficiency as a function of slug size. In addition to this case several key parameters were targeted and changed to note the impact of reservoir mixing on the SP flood. Each of these cases were tested with 351 individual simulations, starting from a waterflood, with an SP slug and polymer buffer size of zero, to a design with 1.0 pore volumes (PV) of SP followed by 3.0 PV of polymer buffer. Testing was done with an increment of 0.10 PV for both chemical slugs. For incremental efficiency to polymer flood, polymer was injected up to a slug size of 4.0 PVI for each case, followed by chase water to the final 5.6 PVI.

In addition to the large-scale testing of each case study, additional simulations were done on smaller chemical slugs, from 0.0 to 0.30 PV each, for many more cases. Here an incremental slug size for testing of 0.02 PV was used. This allowed additional analysis with small injection designs, and showed how slight changes in design are impacted differently by different properties.

The results of the simulations show that the waterflood recovered 37.6% of the original oil in place (OOIP), and the largest designs of pure polymer flood and of both SP and polymer drive recovered 41.3% and 90.9% respectively. These examples as well as a smaller design are shown in Figure 5.1.
Figure 5.1 – Oil recovery factor with various designs, of waterflood, polymer flood of 0.60 PV and 4.00 PV, and SP and polymer buffer designs of 0.30 PV-0.30 PV and 1.00 PV-3.00 PV.

The waterflood and the maximum design size tested of 1.00 PV SP slug and 3.00 polymer buffer represent the two extremes in recovery found in this study. The incremental for each case is defined as the difference in the final volume of oil recovered from the chemical process to that recovered by waterflood, taken at 5.6 PVI. Figure 5.1 reflects only three cases, while the proposed methodology here relies on showing all tested cases on one figure.

5.2 Contour Plots of Efficiency

For the first time we present simulation estimates of SP flooding results as functions of both the SP slug size and polymer buffer size. To do this, contour plots are created for each slug size, with each plot showing one set of parameters. For the base case design, the recovery factor, incremental oil to waterflood and pounds of effective chemical injected are shown in Figures 5.2-5.4.
Figure 5.2 – Recovery factor as a function of SP slug and polymer buffer sizes, % OOIP.

Figure 5.3 – Incremental recovery to waterflood as a function of design, STB.
The most useful contour plots come from combining these plots to show the incremental efficiency of the process.

5.2.1 Use of Incremental Efficiency

Plotting the process efficiency, either with incremental efficiency or with utility factor (UF) has been a helpful tool to determine optimum slug sizes in chemical EOR projects (Laoroongroj et al. 2014), and similarly been used to optimize the slug size in miscible gas flooding (Panda et al. 2009). One of the first studies optimizing slug size of SP flooding plotted various cases of oil recovery with slug size (Jones 1972). This study failed to highlight the slug process, as the slug size was chosen from a continuous injection simulation. In this work, plotting the incremental efficiency of the slug injection process gives us a best-practice methodology to determine the true optimum designs.
Figure 5.5 – Incremental efficiency as a function of SP slug and polymer buffer sizes in pore volumes injected.

Representative of the base case design.

Figure 5.5 shows the key shape of the incremental efficiency, where the largest values occur below an SP slug size of 0.20 PV. To focus in on the most important regions, from this point forward we only consider SP slugs up to 0.50 PV.

From Figure 5.5 many subplots are useful for comparison purposes. Each axis can be isolated, to show the incremental efficiency of a polymer flood, and of a SP flood with no trailing polymer buffer. These plots are shown in Figures 5.6 and 5.7 respectively. Also noted on these diagrams is the economic limit, for the base case of 0.0933 STB/lb. chemical injected that is required for the project to be profitable. Any efficiency above this limit results in an incremental profit per barrel produced, while any efficiency below results in an incremental loss. The two definitions of optimum slug size, maximum incremental efficiency and maximized profits, can be found on these limiting case diagrams as the highest point on the figure, and the last point of intersection of the economic limit, respectively.
For the incremental optimum, where we maximize efficiency, we see no true optimum with respect to polymer flooding, and an optimum SP slug of 0.20 PV. This indicates that additional polymer will not be as effective, while there is a point to which surfactant becomes the most effective. For the economic optimum of each, we see that the polymer flood is optimized at 0.50 PV, while the SP flood with no polymer buffer fails to breakeven, and thus has no economic optimum and should not be conducted.

Previous studies have shown that for polymer flooding, there is no true efficiency optimum in the presence of crossflow (Laoroongroj et al. 2014). It is shown that the utility factor (inverse of incremental
efficiency) is monotonically increasing when there is crossflow, and “more oil can be recovered with larger slug sizes but the efficiency of the polymer solution injection is decreasing (larger UF with larger slug sizes)” (Laoroongroj et al. 2014). This behavior is also seen here for there is no minimum value of polymer necessary for an effect, and polymer is shown to decrease the level of mixing in the fluid. This results in a very small amount of polymer showing incremental recovery, as shown in Figure 5.8, where as little as 2.9 pounds of polymer is shown to increase oil production.

![Graph](image)

**Figure 5.8 – Polymer incremental efficiency at small injection sizes.**

The incremental efficiency curve of the SP slug better reflects the case of miscible gas injection (Panda et al. 2009). Here the utility factor gives a clear optimum, decreasing rapidly to the optimum value and then gradually increasing (Panda et al. 2009). The inverse of Figure 5.9 compares to Figure 5.7 for SP flooding. This shows that the SP slug behaves more like a solvent than the polymer flood. The reasoning is the effect of mixing and the minimum concentration required for efficacy as in miscible gas injection. The CMC compares to the MME/MMP, and the result is that a small amount of injected chemical does not result in the maximum oil recovery until a sufficient amount is injected.
The paramount contour plot of this work is the incremental efficiency as a function of design. To illustrate the successful designs of the project, and to easily determine the two discussed optimum designs, the economic limit was subtracted from the measured efficiency. By subtracting the required efficiency for profit, 0.0933 STB/lb. chemical injected for the base case design, we highlight a region of economic success, as any positive value. This region is circled with a black contour and displayed in Figure 5.10. This figure depicts the resulting contour of the base case design and is used to compare each varied parameter. The two optimum designs are found and shown. The incremental efficiency optimum design is the point of maximum efficiency, ignoring the trivial solution at small slug sizes resulting from the polymer flood incremental efficiency curve shown in Figure 5.8. This optimum is denoted by a blue ‘O’, and is 0.10 PV of SP slug, and 0.50 PV of polymer buffer. The economic optimum is found by the design resulting in the largest volume of oil recovered, inside the zone of economic success. This is marked with a red ‘X’, and is 0.20 PV of SP slug, followed by 2.40 PV of polymer buffer.
Figure 5.10 – Incremental efficiency as a function of SP flood design. Representative of the base case parameters and design, the black line indicates the zone of economic success. The blue O indicates the efficiency optimum design, and the red X denotes the economic optimum design.

Figure 5.10, and all following contour diagrams of incremental efficiency, are filled contour diagrams interpolating between measured values across the tested range. Due to the calculation of incremental efficiency where a waterflood is used to define incremental, there is no data point given at the origin. For zero SP slug and polymer buffer, there is both no incremental recovery to waterflood and no mass of chemical injected, as this design is simply the waterflood. We cannot define an efficiency as we cannot divide by zero mass injected. Therefore there is a region near the origin where there is no data point, thus there is no relation of the incremental efficiency.

5.2.2 Impact of Each Parameter

The effects of mixing on SP flooding were tested by changing one parameter at a time and observing the impacts on the incremental efficiency contours. This section denotes the parameters changed,
and their observed effects. The base case design serves as the comparison for further results, where each parameter is changed one at a time, while all other values are held constant. The base case described in Chapters 3 and 4 is summarized in Table 5.1.

**Table 5.1 – Summary of base case design properties and results.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L$, $h$, $w$</td>
<td>320 ft., 32 ft., 32 ft.</td>
</tr>
<tr>
<td>$V_{DP}$</td>
<td>0.40</td>
</tr>
<tr>
<td>$\lambda_{sd}$, $\lambda_{zd}$</td>
<td>0.50, 0.031</td>
</tr>
<tr>
<td>$S^*$</td>
<td>0.36 meq/ml</td>
</tr>
<tr>
<td>$\alpha_{Input}$</td>
<td>0.0 ft.</td>
</tr>
<tr>
<td>Polymer, surfactant, alcohol cost</td>
<td>$7/lb., $3.4/lb., $1.4/lb.</td>
</tr>
<tr>
<td>$\beta_S$, $\beta_A$</td>
<td>0.49, 0.20</td>
</tr>
<tr>
<td>Total volume injected</td>
<td>5.60 PVI</td>
</tr>
<tr>
<td>Oil price</td>
<td>$75/STB</td>
</tr>
<tr>
<td>Economic limit</td>
<td>0.093 STB/lb. chemical injected</td>
</tr>
<tr>
<td>Incremental optimum</td>
<td>0.10 PV SP, 0.50 polymer buffer</td>
</tr>
<tr>
<td>Economic optimum</td>
<td>0.20 PV SP, 2.40 polymer buffer</td>
</tr>
</tbody>
</table>

*Added dispersivity*

To increase the amount of mixing in the simulation we added 2.5 feet of dispersivity to the base case model. The resulting contour is shown in Figure 5.11.
Figure 5.11 – Incremental efficiency contour of $V_{dp} = 0.40, \ S^* = 0.36 \text{ meq/ml, } \alpha_{\text{input}} = 2.5 \text{ ft., } \lambda_x = 0.50$.

Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 1.90 PV polymer buffer).

The added dispersion shifts the economic zone to the right, showing that a larger SP slug size is required for this larger reservoir mixing. As the amount of SP required increased, the required polymer drive decreased in size. The incremental optimum now lies at 0.10 SP, 0.40 polymer buffer, with the economic optimum at about 0.20 PV SP and 1.90 PV polymer buffer. The economic zone indicates the changed result as a better metric than the optimum designs, but the polymer buffer decreases in size by 0.10 PV and 0.50 PV in each case. This result shows that in the SP flooding process, the two different slugs, made of different chemicals, are affected differently by the same change in mixing.

Dykstra-Parsons coefficient

It was shown that the level of heterogeneity in the model greatly impacts the amount of mixing, so the second parameter tested to show the effects of mixing on the SP flooding process was the Dykstra-
Parsons coefficient, $V_{dp}$. Figure 5.12 shows the results of incremental efficiency in a very heterogeneous case, with a $V_{dp}$ of 0.80.

![Contour Diagram](image)

**Figure 5.12 – Incremental efficiency contour of $V_{dp} = 0.80$, $S^* = 0.36 \text{ meq/ml, } \alpha_{input} = 0.0 \text{ ft., } \lambda_{sp} = 0.50$.**

**Incremental optimum (0.00 PV SP, 0.10 PV polymer buffer), economic optimum (0.00 PV SP, 0.40 PV polymer buffer).**

This heterogeneous case shows that the permeability variances dominate the flood. The economic region is limited to the cases of polymer flooding only, with the incremental efficiency limited to the trivial solution of the minimum tested polymer slug size, and the economic optimum given at 0.00 PV SP and 0.40 PV polymer flood. The incremental efficiency is much lower and below the economic limit for all SP flooding cases. This shows in exceptionally heterogeneous reservoirs the effects of surfactant flooding are minimized due to the poor sweep efficiency in the reservoir. When the polymer mobility effects are dominated by thief zones of high permeability the resulting boost in sweep efficiency and volume of oil
contacted are minimized, so the surfactant is unable to contact enough trapped oil, for the only oil it contacts has been subject to previous waterflooding.

Permeability correlation length

The distribution of permeability values and heterogeneity in the reservoir influences the amount and effects of mixing, as do the variance of these samples. To change the characteristics of the permeability distribution and observe the effects on design, the permeability correlation lengths were altered and tested. For this case the correlation length in the x-direction was changed by a factor of ten, increasing to 5.0. This results in a much more layered reservoir, with long zones of similar permeability values in the horizontal direction of flow.

Figure 5.13 – Incremental efficiency contour of \( V_{dp} = 0.40, \; S^* = 0.36 \text{ meq/ml}, \; \alpha_{input} = 0.0 \text{ ft.}, \; \lambda_{xp} = 5.00. \)

Incremental optimum (0.10 PV SP, 0.60 PV polymer buffer), economic optimum (0.20 PV SP, 1.80 PV polymer buffer).
Figure 5.13 shows results similar to the base case design, with the economic zone slightly reduced in size. Here the variability in permeability is low enough that the increased channeling effects are not enough to dominate the mixing effects. The polymer buffer becomes slightly more effective, with the incremental optimum given as 0.10 PV SP, and 0.60 PV polymer buffer, and the economic optimum at 0.20 PV SP and 1.80 PV polymer buffer.

**Optimal salinity**

One parameter chosen to observe the design changes based on the efficacy of the surfactant in the SP slug is the optimal salinity. Here the effects of the surfactant are hindered by the lowered optimal salinity to 0.24 meq/ml. This changes the salinity gradient experienced across the SP slug, and regions that had been both over the CMC and at optimal salinity may now not cross optimal salinity.

Figure 5.14 – Incremental efficiency contour of $V_{sp} = 0.40$, $S^\ast = 0.24$ meq/ml, $a_{input} = 0.0$ ft., $\lambda_{sp} = 0.50$.

Incremental optimum (0.10 PV SP, 1.3 PV polymer buffer), economic optimum (0.10 PV SP, 2.5 PV polymer buffer).
Figure 5.14 shows the project is hindered when the scale of the salinity gradient is decreased. The incremental efficiency is lower across the range of tested designs, and the zone of economic success is decreased to include less SP than the base case design. Here the project relies heavily on the polymer buffer, with the incremental optimum at 0.10 PV SP and 1.3 PV polymer buffer, with the economic optimum at 0.10 PV SP and 2.5 PV polymer buffer. As the surfactant is hindered the polymer buffer becomes more important to the overall efficiency.

These tested cases all show that the three main components of a surfactant-polymer flood, the SP slug, the polymer buffer, and the salinity slug, are all affected differently. When one parameter or the amount of mixing is changed, the effects are different for each fluid, causing a complicated relationship in optimizing the project design.

5.3 Compositional Analysis

A compositional analysis was performed, taking specific reservoir cross sections at similar times. Comparing these results to the incremental efficiency results displays a picture of the nature of flow and impacts of each parameter.
Added dispersivity

Figure 5.15 – Surfactant and polymer concentrations (volume fraction, wt. %) in the reservoir at \( t_D \) of 1.50 PVI, for the design of 0.10 PV SP, 0.50 PV polymer buffer. (a.) and (c.) denote surfactant concentration, (b.) and (d.) polymer concentration. (a.) and (b.) have no additional mixing while (c.) and (d.) have \( \alpha_{\text{Input}} = 2.50 \) ft.

Figure 5.15 shows the surfactant and polymer concentrations of the base case design and in the presence of increased mixing. The figures show the surfactant to be noticeably spread out and smeared vertically compared to the base case. Polymer is less affected, still showing signs of increased mixing across layers. Figure 5.15 supplements the findings of Figure 5.11, as the two fluid components are affected differently by the same change in mixing, with the surfactant experiencing a greater change. This verifies the shift to the right seen by the economic zone, and the decrease in polymer buffer size in the optimal design, as the polymer is able to sweep more of the reservoir and less polymer is needed for the same effect.

Dykstra-Parsons coefficient

As we increase the level of heterogeneity in the model it begins to dominate the effects of the chemicals and the channeling through high permeability regions will dominate any mobility effects. Figure 4.12 showed that the economic region is limited to small polymer flooding cases, as the injected polymer and surfactant do not reach enough of the reservoir to reach an economic success. Figure 5.16 shows this
channel-dominated flow, as defined and used by Connolly and Johns (2016). Channel-dominated flow occurs when little dispersion is present due to flow occurring only through high permeability regions (Connolly and Johns 2016). The transition from dispersion-dominated flow, where enough heterogeneity mixes the fluid front across the reservoir, to channel-dominated flow is given by Waggoner et al. (1992).

Figure 5.16 – Compositional analysis of surfactant and polymer across a very heterogeneous reservoir. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %).

**Permeability correlation length**

A layered reservoir with longer correlation lengths along the primary flow direction resulted in similar incremental efficiencies to the base case design. In a layered reservoir, if the variance in $V_{dp}$ is low, dispersion-dominated flow can still exist, where mobility changes sufficiently increase sweep. This allows economic success of the SP flood and an economic zone of comparable size to the base case design. The chemical components of surfactant and polymer are shown in Figure 5.17 to follow similar flow paths and are affected similarly by the increased correlation length.
Figure 5.17 – Compositional analysis of surfactant and polymer across a layered reservoir with increased permeability correlation length in the x-direction. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %).

**Optimal salinity**

Section 2.9.1 showed the importance of salinity to the phase behavior of surfactants. As the salinity gradient experienced by the injected fluid becomes less effective at passing through the optimum, the drop in interfacial tension and fluid mobility effects will decrease. This hinders the flow of surfactants compared to optimal conditions, and the injected chemical will not spread as effectively, contacting a smaller volume of oil. Figure 5.18 shows the polymer concentrations flowing similarly to the base case, while the surfactant concentration is limited to a smaller area and has mixed less in the reservoir.
Figure 5.18 – Compositional analysis of surfactant and polymer concentration with a lowered optimal salinity of 0.24 meq/ml. (a.) Shows surfactant concentration (volume fraction) and (b.) shows polymer concentration (wt. %).

We see that the economic zone for this case is decreased and focuses the design to the polymer buffer and away from the SP slug.

5.4 Economic Results

When designing any chemical flooding process, the economic status of the project is vital, for the floods involve injecting expensive chemicals and are typically large-scale projects. The driving tool of analysis, the incremental efficiency, is heavily dependent on economics for three main prices, the oil price, the cost of polymer, and the cost of surfactants. Here each of the three main cost factors is shown across a wide range of values to observe how the optimal designs, and incremental efficiencies can change.

5.4.1 Effect of Oil Price

Oil is a notorious commodity for changing value and going through cycles of high and low prices. The oil price therefore is a significant factor in any petroleum engineering application, as it is subject to wide fluctuations, and determines the revenues of the project. The effect of oil price on this study does not
change the shape of the incremental efficiency results, but only the economic limit of the project. With this, the incremental efficiency optimum for each case will remain the same no matter the oil price, but the zone of economic success and the economic optimum design will certainly change. A similar range of oil prices are tested as done by Sieberer et al. (2017).
Figure 5.19 – Incremental efficiency and optimum designs with a changing oil price. (a.) $50/STB, (b.) $60/STB, (c.) $70/STB, (d.) $80/STB, (e.) $90/STB, (f.) $100/STB.
As the economic limit is lowered with increasing oil price, the economic zone quickly expands. The economic optimum moves with the expanding zone, and quickly lies outside of the designs tested here (Figure 5.19 (d.) and (f.)).

The economic optimum design changes substantially with the oil price, and is plotted at various oil prices in Figure 5.20. This figure describes the optimum design of both the SP slug and polymer buffer at any oil price for the base case design. This is limited to this specific reservoir, permeability distribution, and parameters and assumptions, like the absence of adsorption. By assuming a linear trend for each slug with oil price, a function is plotted allowing extrapolation of these data points to find the necessary oil price to inject each slug. The necessary oil price for injection of each slug indicates the oil price that the trend line reaches a slug size of 0.0 PV. For the base case design the necessary oil price for polymer is $7.37/STB, and for surfactant-polymer $31.07.

![Diagram showing economic design of SP and polymer buffer slug sizes for the base case design as a function of oil price.](image)

Figure 5.20 – Economic design of SP and polymer buffer slug sizes for the base case design as a function of oil price.
### 5.4.2 Effect of Chemical Costs

Just as the oil price can determine the success and design of a project, the incremental cost of injecting chemicals plays a significant role. Chemical EOR projects are the least popular form of EOR today, due to their large chemical cost (Koottungal 2014). In an SP flood, the two driving costs are the cost of polymer and the cost of surfactant, assuming that the injection equipment is already in place. This section denotes the impact of these two costs on the incremental efficiency and economic standing of the project. Unlike oil price, the chemical cost, or ratio of the associated chemical costs, is included in the calculation of incremental efficiency through $\beta$. Therefore, changing chemical costs will directly alter the shape of the contours, as well as change the economic limit for breakeven. Chemical costs can change with time, and with location of the project. The ideal field will be in close proximity to a chemical supplier, greatly lowering the associated costs.

**Effective Polymer Cost**

Our definition of effective polymer cost encapsulates the cost of the polymer chemical per pound as well as all other project costs involved in field development and application. Changing this cost depends on several important parameters and assumptions. Here we select a few sample points to illustrate but these values are not based on any specific costs or new assumptions.
Figure 5.21 – Incremental efficiency and optimum designs with a changing effective polymer price. (a.) $3/lb. (b.) $7/lb., (c.) $11/lb., (d.) $15/lb., (e.) $19/lb., (f.) $37/lb.
In Figure 5.21 the size of the economic zone is strongly dependent on polymer cost. The zone decreases until finally reaching a single point at a cost of $37/lb. At this high price the economic and incremental optimum designs are identical, as only one design results in a profit. At a low enough chemical cost the economic optimum design lies outside the region of tested values, and is displayed along the upper bound for polymer buffer size in Figure 5.21 (a.). As price increases the economic zone decreases along the polymer buffer axis and the two selected optimums follow. Figure 5.21 (c.) and (d.) prove that our base case design can be profitable with an SP flood at the total incremental chemical cost as seen in a true field application (Sieberer et al. 2017).

**Surfactant Cost**

Surfactants are the most expensive chemical we inject to recover oil, and based on the amount required to recover one STB of oil can reach prices near that of the oil we are trying to produce (Taber 1990). This work defines surfactant cost as purely the chemical costs themselves. This definition limits the flexibility of the price, but we present six alternative surfactant costs in addition to our base case design to show the effects on our incremental efficiency model.
Figure 5.22 – Incremental efficiency and optimum designs with a changing surfactant price. (a.) $2/lb., (b.) $3/lb., (c.) $4/lb., (d.) $5/lb., (e.) $6/lb., (f.) $7/lb.
With low surfactant costs (Figure 5.22 (a.)) we see a large economic zone, and a large economic optimum design. As the price increases the economic zone decreases in size until only encapsulating the polymer flood, as shown in Figure 5.22 (f.). Here the incremental efficiency optimum design is changed slightly with surfactant cost but only at extreme values, at $7/lb.

**5.5 Impacts of Mixing**

Sections 5.2 through 5.3 are designed to show the effects of mixing on the process and design of SP floods. This section further analyzes these effects on the fluids in the reservoir. Increased dispersion results in a shift of the economic zone to require a larger SP slug size, and a lower polymer buffer slug size. This result is similar to that of a miscible flood, where a larger slug size is often required for increased mixing. Here, the mixing spreads out the surfactant across the reservoir and increases sweep efficiency.

The optimum slug designs are shown to change with increased mixing, showing that accounting for mixing directly impacts the design of an SP flooding project. The economic optimum designs change with oil price, and are compared to those of the base case design in Figure 5.23 as the dashed lines that have been added to Figure 5.20.
Here the trend for optimum polymer buffer slug size shows a decreased value across the entire range of tested values, while the SP slug has been increased or decreased dependent on oil price. The required oil price for each slug has increased to $30.50 for polymer buffer and $38.83 for SP for the case with input dispersivity.

Figure 5.15 shows that mixing results in two effects also observed in miscible flooding, increased sweep of the injected fluid and decreased effective strength or concentration (Stalkup 1990). When injecting substantially above the critical micelle concentration (CMC), this added mixing improves recoveries and improves the incremental efficiency of the process. When close to the CMC the increased sweep effect is dominated by the loss in concentration and mixing becomes detrimental to recoveries, as shown in Figure 5.24.
Figure 5.24 – Effect of mixing near the CMC. (a.) Surfactant concentration (vol. fraction) with no added mixing and a CMC of 0.01, (b.) surfactant concentration with 2.5 ft. added dispersion.

Here the CMC is raised to 0.01 volume fraction, one third of the injected concentration. At a $t_D$ of 1.50 PVI the number of grid-blocks above the CMC decreases, which adversely impacts the SP process. The maximum surfactant concentration of any point in the reservoir drops from 0.010 to 0.0082 (volume fraction), where at no location is the surfactant concentration above the CMC. This inhibits the phase behavior necessary for the surfactant to minimize IFT, and the incremental efficiency drops from 0.060 to 0.058 STB/lb. chemical. This result is similar to that shown in miscible flooding when injecting sufficiently above the MME results in mixing as a beneficial process, but injecting near the CMC mixing is detrimental (Stalkup 1990).

Figures 5.15-5.18 show that mixing affects polymer differently than surfactant concentrations. Surfactant concentrations are more susceptible to noticeable sweep and concentration changes. This is a key difference in chemical EOR compared to miscible gas flooding, where mixing affects the one slug of interest. In fact, mixing affects a third slug, as shown in Figure 5.24.
Figure 5.25 – Salinity slug impacted by reservoir mixing. (a.) No added mixing, (b.) 2.5 ft. added dispersion.

Figure 5.25 shows that in addition to the surfactant and polymer concentrations being affected by increased dispersion, the salinity slug created by the injection conditions is also subject to sweep and concentration changes as a result of mixing. The change in salinity impacts phase behavior and the efficacy of the flood. Here the injected fluid is well below the optimal salinity, creating a large gradient to ensure the optimum is crossed, as displayed by the injected salinity being well below the optimal salinity in Figure 4.6. Because of this salinity slug design, the concentration changes are dominated by the increased sweep, and there is an increase in the number of grid-blocks at or below the optimal salinity, from 1570 (76.6% of the reservoir), to 1636 (79.9%). At a design of 0.20 PV SP and 0.50 PV polymer buffer, there is an increase in incremental efficiency from 0.1055 to 0.1075 STB/lb. chemical.

We would expect the opposite results to be true when the size of the salinity gradient is decreased. When the optimal salinity is lowered to 0.21 meq/ml, there is a narrow window to obtain optimal conditions created by the salinity gradient, and mixing is therefore expected to cause the concentration losses to dominate the increased sweep. The proximity to a concentration limit of salinity emphasizes concentration
losses to sweep effects. Figure 5.26 shows the small gradient created by the injection scheme and the optimal salinity, $S^*$. 

![Diagram showing injection scheme and salinity gradient](image)

**Figure 5.26** – Decrease optimal salinity, 0.21 meq/ml, resulting in small salinity gradient.

![Graph showing salinity slug with reservoir mixing](image)

(a.) No added mixing,

(b.) 2.5 ft. added dispersion.

**Figure 5.27** – Salinity slug with a low optimal salinity impacted by reservoir mixing. (a.) No added mixing,

(b.) 2.5 ft. added dispersion.

Instead of seeing results similar to the case close to CMC where the compositional changes dominate changes in sweep, in Figure 5.27 mixing is once again a beneficial process due to the increased
sweep. Incremental efficiency is increased from 0.0765 to 0.0897 STB/lb. chemical in this case, as the number of grid-blocks crossing optimal conditions increased from 450 (22.0%) to 542 (26.5%).

The difference between these two processes, where our injection conditions are close to the limiting factors, is the size of the slug and what follows them upon injection. In testing the effects of CMC, we have a small SP slug followed by a polymer buffer with no surfactant. In the salinity slug, low salinity is first injected with the SP slug and again in the polymer buffer. This large effective salinity slug which is the combined size of the SP slug and polymer buffer, causes enhanced sweep to dominate the concentration loss. At smaller salinity slugs, through the use of smaller polymer buffers and SP slugs, this is no longer the case.

Figure 5.28 – Mixing effects shown as detrimental or as beneficial dependent on the size of injected slugs.

Shown as a function of SP and polymer buffer slug sizes.

Figure 5.28 shows where mixing applied to the base case design can be beneficial or detrimental to overall incremental efficiency. This plot was created by comparing the incremental efficiency of the base
case design to that with an increased dispersivity of 2.5 ft. Due to the design, the spreading effects dominate concentration effects, and mixing is beneficial at small SP slug sizes. This result is unique to chemical EOR processes with multiple slugs of injection, as the nature of mixing is dependent not only on the fluids themselves, on each fluid separately, but also on the sizes of each and of how these slugs combine.

To investigate how and why each fluid component is impacted differently by mixing, the methodology of determining dispersivity from fitting the CDE to results was used. The methodology of Chapter 3 was expanded to find a dispersivity factor of each fluid component. The methodology of isolating $\alpha_{\text{Permeability}}$ involves the use of a single-phase tracer, with a unit mobility ratio. During any EOR process, whether miscible gas or chemical flooding, we typically do not have unit mobility ratios, and care about the spreading of each component in the reservoir. To test how different fluids can affect the measured dispersion, three cases were done using continuous injection. These are summarized in Table 5.2.

<table>
<thead>
<tr>
<th>Chemical</th>
<th>Injection Fluid</th>
<th>$M^0$</th>
<th>Dispersivity Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polymer</td>
<td>Polymer – 1800 ppm</td>
<td>0.047</td>
<td>0.290</td>
</tr>
<tr>
<td>Polymer</td>
<td>Polymer – 600 ppm</td>
<td>0.348</td>
<td>0.575</td>
</tr>
<tr>
<td>Tracer</td>
<td>Single phase tracer</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Surfactant</td>
<td>SP slug – 600 ppm polymer</td>
<td>1.149</td>
<td>1.463</td>
</tr>
</tbody>
</table>

The dispersivity factor is defined as the measured $\alpha_{\text{Total}}$ at a point for each component divided by $\alpha_{\text{Total}}$ found using a single-phase tracer,

$$\text{Dispersivity Factor} = \frac{\alpha_{\text{Total, fluid}}}{\alpha_{\text{Total, tracer}}}. \quad (5.1)$$

A dispersivity factor below unity indicates a decrease in dispersion by the fluid compared to a tracer with a mobility ratio of 1, and a dispersivity factor above unity indicates the fluid increased dispersion. Table 5.2 shows that polymer and surfactant both have different mobility ratios and are affected differently by
mixing. The mobility ratios are found by the endpoint relative permeability values, and the viscosity measured in the simulations. These ratios and their endpoint mobility ratios are plotted in Figure 5.29.

![Graph showing dispersivity factor and endpoint mobility ratio](image)

**Figure 5.29 – Dispersivity Factor and endpoint mobility ratio.**

Figure 5.29 shows an increasing trend of dispersivity factor with mobility ratio. This implies that favorable mobility ratios not only delay breakthrough (Lake et al. 2014), but decrease the level of mixing caused by reservoir heterogeneity. Adverse mobility ratios, like in miscible gas flooding, increase the level of mixing. This makes them more sensitive to changes in dispersion and $a_{\text{permeability}}$ increases as the effects become magnified at large mobility ratios.

From the same continuous SP injection where surfactant dispersivity factor was calculated as 1.46, the polymer dispersivity factor is 0.73. This shows that even though they are injected together in the same slug, each chemical behaves differently, while polymer reduces mixing and surfactant magnifies it. This adds to the result that surfactant and polymer in SP flooding are affected differently by the same changes in mixing, where the surfactant sees greater effects and the polymer is less sensitive to mixing.

A key difference with the effects of dispersion on chemical flooding applications and miscible gas flooding, is that in miscible gas flooding mobility ratios are typically around 25 (Connolly and Johns 2016), while in chemical flooding near or below unity (Lake et al. 2014). These mobility differences change how
mixing impacts each process, where it can be minimized in certain aspects of chemical flooding but is magnified by injected gas in miscible floods. These results can be plotted alongside results found from miscible gas literature, in Figure 5.30.

![Figure 5.30](image)

**Figure 5.30** – Comparison of dispersivity factor to results seen in other studies at adverse mobility ratios.

Sources: Garmeh et al. (2009) and Connolly and Johns (2016).

Figure 5.30 shows that in general an increasing trend is supported of dispersivity factor with mobility ratio. The data provided by Connolly and Johns (2016) shows data points at mobility ratios of 10, 100 and 1000. The drawn curve indicates that dispersivity factor increases with favorable mobility ratios, until reaching an adverse mobility ratio where dispersivity decreases with increasing mobility ratio. This decrease results from the channel-dominated flow environment, as the injected fluid quickly travels through a small zone, decreasing the impacts of dispersion. As the mobility ratio approaches zero, the dispersivity factor also approaches zero.

### 5.6 Model Limitations

These results are limited to the designed case study, which was designed for illustrative purposes and not based on a physical reservoir. These results thus are lacking a detailed analysis with three-dimensional flow, where mixing would have a greater effect. The key assumptions listed in Chapter 3.2.1
and 4.2 show the limitations for direct comparison, but the general trends will apply to similar cases. The results listed in this chapter show contrast to those shown in other studies where dispersion was ignored.

In Chapter 5.6.1 we highlight these differences and expand on the reasoning behind the differences, and in 5.6.2 focus on the key parameters that limit the applicability of this model and results.

### 5.6.1 Differences from Literature

Extensive research has been undertaken on the effects of mixing on miscible gas flooding (Walsh and Orr 1990; Johns et al. 1994; Stalkup 1998; Solano et al. 2001; Garmeh 2010), but little has been applied to the case of SP flooding. Lake and Helfferich (1978) studied the effects of mixing on SP flooding, but only how dispersion impacts the effective salinity and ion concentration of the fluid, impacting the process. Several studies concluded that mixing is not an important process, and likely will not change the design or results of the SP flood (Wright et al. 1987; Clifford 1988; Rai 2008).

Wright et al. (1987) studied the flow instabilities of a two-layered system with multiple slug injection. The authors used two homogenous layers with no crossflow, failing to represent the heterogeneous nature of physical reservoirs. Dispersion was stated as an important parameter for a minimum economical slug size, but due to the favorable mobility ratio designed for chemical EOR processes, “fluid mixing is unlikely to be deleterious to oil recovery” (Wright et al. 1987). The aforementioned results of this chapter show that this assumption is not accurate and mixing can have a significant impact on oil recovery.

Clifford (1988) studied the simulation of slug behavior with polymer and micellar floods, with coarsening grids and increasing numerical dispersion. A polymer slug is injected into a layered reservoir and simulated with different grid-block sizes (Clifford 1988). The effluent and oil recovery results are compared, and it is found that “coarse grids will substantially distort the effluent profile of polymer and other fluids, and yet can still in many cases yield a relatively accurate assessment of incremental oil recovery” (Clifford 1988). These conclusions are based on simulating two slug sizes at different scales,
with numerical dispersions of 20 ft. and 100 ft., and concluding that the difference in the incremental oil recovery factor of 21% and 18% is negligible. We contest that these results not only fail to reach the intended conclusion but support the results of this chapter, that mixing has a significant impact on the SP flooding process and design.

Rai (2008) simulated three cases of an SP flood with different grid-block sizes, claiming three levels of numerical dispersion were used where “changes in dispersion were actually modeled by changes in the numerical dispersion, which is done by changing the number of grid-blocks” (Rai 2008). Here a total-variation diminishing (TVD) scheme was used in place of single-point upstream weighting. The presence of this scheme changed the contribution of numerical dispersion where it is no longer a linear function of grid-block size. TVD is used as a flux-limiting scheme, to achieve higher order accuracy without the common oscillations, thus the numerical dispersion resulting of a TVD scheme is significantly lower, even approaching that of an analytical solution (Connolly 2013). The findings of Rai (2008) thus do not reflect any significant changes in reservoir mixing, thus should all result in similar recoveries.

5.6.2 Key Factors

Several parameters of these results are of interest for future expansion and influenced the given results. First the design optimization relied on setting three chemical cost values, for the polymer, surfactant and alcohol injected. Simplifying the entire field costs of Capex and Opex into one incremental parameter relies on field-specific assumptions to be made. This definition allowed the simple definition of other chemical costs and the incremental efficiency to be calculated using a single chemical mass based on chemical cost ratios. Before applying these results and this methodology to any field these values must be determined and well understood.

The optimized designs based on incremental efficiency and on economic profit rely on a fixed concentration of the fluids upon injection. Similar to gas flooding where we optimize the enrichment (Lake et al. 2014), true optimization of slug design would involve the concentration of each chemical as well as
slug size in pore volumes. This assumption resulted in true slug size optimization as a function of each chemical slug size, and not in the total mass injected.

A major assumption of this study and these results is the absence of adsorption, for surfactant and polymer. Adsorption is a significant factor detrimental to chemical flooding (Pope et al. 1979). The results of this research indicate optimum slug sizes beyond those typically found and used (Lake et al. 2014), and this may result from the exclusion of adsorption. Two tests were done to show the impact of accounting for adsorption, both on the optimization of design and slug sizes, and on the effects of mixing. The adsorption parameters used are similar to those used by Rai (2008), excluding the adsorption reduction resulting from ASP flooding.

Table 5.3 – Adsorption input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>UTCHEM Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surfactant adsorption parameter, dimensionless</td>
<td>AD31</td>
<td>3.3</td>
</tr>
<tr>
<td>Surfactant adsorption parameter, (meq/ml)$^{-1}$</td>
<td>AD32</td>
<td>0.5</td>
</tr>
<tr>
<td>Surfactant adsorption parameter, volume of water/volume of surfactant</td>
<td>B3D</td>
<td>1000</td>
</tr>
<tr>
<td>Polymer adsorption parameter, dimensionless</td>
<td>AD41</td>
<td>1.4</td>
</tr>
<tr>
<td>Polymer adsorption parameter, (meq/ml)$^{-1}$</td>
<td>AD42</td>
<td>0.5</td>
</tr>
<tr>
<td>Polymer adsorption parameter, volume of water/weight % of polymer</td>
<td>B4D</td>
<td>100</td>
</tr>
<tr>
<td>Competitive adsorption parameter</td>
<td>FADS</td>
<td>0</td>
</tr>
<tr>
<td>Reference permeability, md</td>
<td>REFK</td>
<td>500</td>
</tr>
</tbody>
</table>

The impact of adsorption to the base case design reduces the optimum polymer buffer and the shape of the economic zone.
Figure 5.31 -- Incremental efficiency contour of $V_{VP} = 0.40$, $S^* = 0.36$ meq/ml, $\alpha_{Input} = 0.0$ ft., $\lambda_s = 0.50$ with adsorption introduced. Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 0.90 PV polymer buffer).

The addition of mixing to the adsorption case displays a lesser impact to dispersion as shown in the base case design. The economic zone continues to decrease in size, while the optimum polymer buffer in terms of economics now falls to 0.70 PVI in Figure 5.32.
Figure 5.32 -- Incremental efficiency contour of $V_{sp} = 0.40$, $S^* = 0.36$ meq/ml, $\alpha_{input} = 2.5$ ft., $\lambda_{x_p} = 0.50$ with adsorption introduced. Incremental optimum (0.10 PV SP, 0.40 PV polymer buffer), economic optimum (0.20 PV SP, 0.70 PV polymer buffer).

The economic optimum slug sizes now reflect similar values to those seen in the field historically (Lake et al. 2014). This indicates an opportunity for further research into the effects of adsorption on mixing and the results shown in this thesis. The significant impact of adsorption shown by Figures 5.31 and 5.32 result from the extremely large quantities of each chemical that have been adsorbed. At the economic optimum design shown in Figure 5.31 of 0.2 PV SP slug and 0.90 PV polymer buffer, 53.9% of the surfactant injected was adsorbed, while 83.9% of the polymer was adsorbed. These are extremely high values for adsorption and reflect why the polymer buffer was affected so greatly by the inclusion of adsorption.

Another difference from literature in this study is the design of the salinity gradient in the injection scheme. A low salinity chemical slug is injected into a high salinity reservoir, but the SP and polymer buffer slug sizes are injected at an identical effective salinity of 0.20 meq/ml, both below optimum. Previous works
have injected the SP slug at the optimum salinity, and followed it with a polymer buffer below optimum (Rai 2008). A case with this salinity design is indicated in Figure 5.33, and the resulting contour plot shown in Figure 5.34.

Figure 5.33 – Salinity injection design with the SP slug injected at optimum salinity, followed by a polymer buffer below optimum.
Figure 5.34 – Incremental efficiency contour of $V_{pp} = 0.40$, $S^* = 0.36$ meq/ml, $\alpha_{Input} = 0.0$ ft., $\lambda_x = 0.50$ with tapered salinity injection scheme. Incremental optimum (0.10 PV SP, 1.10 PV polymer buffer), economic optimum (0.10 PV SP, 3.00 PV polymer buffer).

Here we see that the polymer buffer becomes increasingly economic, and the economic optimum now lies outside of the tested range, and the incremental optimum occurs with a very large polymer buffer.

5.7 Conclusions

This chapter showed the results of the simulations designed to show the effects of mixing on surfactant-polymer flooding. Thousands of UTCHEM simulations were used for this display. These effects were shown in a variety of ways, and the main conclusions of this chapter include:

1. Incremental efficiency, incremental STB/lb. of chemical injected, can be plotted as a function of surfactant-polymer and polymer buffer slug design.

2. Optimal designs of process efficiency and of economic profit can be found using incremental efficiency and the economic limit, derived from chemical costs and the value of oil.
3. Reservoir mixing is shown to increase optimal SP slug design size and can be beneficial or detrimental to the overall process.

4. Surfactant and polymer are affected differently by the same increases in mixing.

5. Economic costs and parameters play a significant role in determining optimum designs. Both efficiency and economic optimums are strong functions of chemical costs.

6. Mixing-caused sweep changes can dominate the mixing-caused weakening of injected fluids, and this interplay of effects changes depending on the slug size design.

7. Mixing impacts three different slugs and three components of injected fluid in SP flooding, of the SP slug, the polymer buffer, and of the salinity slug created by injection conditions. All three are affected differently and impact the overall incremental efficiency.

8. Mixing in SP flooding shares similarities to mixing in miscible gas flooding but has significant key differences.

9. Analysis of different reservoir fluids allow fluid dispersivity factors to isolate how different components are affected by mixing. Mobility ratio is shown to greatly impact measured dispersion, and the dispersivity factor approaches zero with a mobility ratio of zero.
Chapter 6: Summary, Conclusions and Recommendations

6.1 Summary

Hydrodynamic dispersion is a scale dependent process consisting of molecular diffusion and dispersion. Dependent on the heterogeneity and properties of the reservoir, dispersion is typically simulated through numerical dispersion. Numerical dispersion results from the truncation error in solving finite differences in reservoir simulation, which is dependent on grid-block size. As we introduce the grid-block assumption to our reservoir, we simplify local heterogeneities and introduce error. Large blocks overestimate the physical level of dispersion through numerical dispersion but reduce the dispersion contributions from permeability distributions.

Surfactant-polymer flooding can show high displacement efficiency by lowering the interfacial tension of oil and water through microemulsion phase behavior. Phase behavior is dependent on component concentrations and salinities, which are both susceptible to reservoir mixing. Mixing causes the injected fluid to spread and decreases its effective strength. Dispersion can affect the best choice of chemical slug sizes, but to date there is a lack of understanding of its impact. Dispersion effects have been studied in miscible gas flooding but largely unaccounted for in chemical flooding design. The high cost of surfactant-polymer flooding necessitates the use of chemical slugs, where success can be determined by the slug size selection.

The main objectives of this research were to:

1. Investigate the impacts of reservoir mixing on the process of surfactant-polymer flooding.

2. Present insight on selecting an optimum injection design in slug sizes of both surfactant-polymer, and of the polymer buffer typically used.

3. Compare the mixing effects seen with surfactant-polymer flooding to those seen in miscible gas flooding.
4. Determine the dispersivity contribution of heterogeneous permeability distributions at incrementally larger block size and note the effects of upscaling.

5. Determine the largest grid-block size in the primary flow direction that will represent physical levels of reservoir mixing in simulations, with numerical dispersion and permeability driven dispersion.

A methodology of isolating dispersivity contributions from various processes is given to observe the proposed decreasing dispersion from permeability with upscaling. With no current relations for dispersion values owing to permeability variations with block size, it was hypothesized that numerical simulation would allow characterization and determination from a total simulated dispersivity. The total simulated dispersivity was equated with physical mixing and allowed optimization of grid-block design.

The numerical simulations in this thesis were designed to highlight the effects of mixing on the process and design of surfactant-polymer flooding. Dispersion was altered by inputting dispersion directly and by changing the permeability distribution in terms of variance and correlation. Effects of mixing were observed both compositionally with space and in terms of process efficiency and economic design. It was hypothesized that process efficiency could determine the optimal design by two definitions, efficiency and economic profit.

6.2 Conclusions

Fine-scale simulation and upscaling of effective grid-blocks allows the isolation of the dispersion contribution of heterogeneous permeability distributions. Permeability driven dispersion rapidly declines with upscaling, showing the importance of grid-block design. The dual nature of the grid-block assumption is shown quantitatively. Dispersion is shown to be sensitive to heterogeneity and vertical permeability ratio, while extrapolation to a grid-block size of zero gives a physical value of dispersion in the reservoir. Two grid sizes match simulated dispersion to physical values, allowing optimal grid selection to be found for each permeability distribution. Application to a chemical flood displays how the mobility ratio for each
component impacts the fluid dispersivity factor. The methodology reduces computational time and uncertainty in project design.

This research shows for the first time a plot of different contributors to dispersion with grid-block size. This highlights the importance of each and allows additional analysis to focus on the sources of modeled dispersion. By optimizing our grid-block selection through dispersion, we allow an improved method of characterizing a physical process in our simulations, while reducing the time and cost necessary to simulate through computation of fine models.

The numerical simulation of surfactant-polymer floods in an example reservoir indicates the importance of dispersion on the efficacy of the injected chemical and on design of optimal slug sizes. Calculating the incremental efficiency of the process as a function of surfactant-polymer slug size and polymer buffer slug size can determine the optimal design. Finding the maximum return in oil volume per mass of chemical injected gives the efficiency optimum design. Application of an economic limit of efficiency shows a limiting economic region for continued injection to increase NPV and gives the best slug size economically.

As dispersion changes each injected chemical is affected differently. In dispersion-dominated flow, the increased sweep due to spreading is beneficial for overall recovery. Channel-dominated flow with high permeability variances reduces efficiency. The effect of mixing is unique to each chemical slug, of polymer, surfactant and salinity; this is different from miscible gas flooding where only one slug is impacted by dispersion. Surfactants are shown to magnify the effects of dispersion, similar to the effect in miscible gas floods, while polymers minimize the effects. The injection design, in slug size and proximity to both critical micelle concentration and optimal salinity, determines whether sweep or concentration changes dominate. Optimal designs are extremely sensitive to the price of oil and cost of each chemical injected.

Dispersion is shown as an important parameter to study in our surfactant-polymer simulations, as it has been previously overlooked. Through observing mixing and the effects of several parameters the best
practical design of the flood is found. By maximizing profits with slug size design, the likelihood that surfactant-polymer flooding application would be an economic success in field applications increases. By learning about what can impact this process, and how we can account for these impacts, surfactant-polymer flooding gets closer to a viable technique to increase oil recovery economically.

6.3 Recommendations

This work provides initial analysis on the impacts of dispersion to surfactant-polymer flooding and provides understanding of dispersion in numerical simulation. The following recommendations are provided for future work:

1. This study introduced several assumptions that were constant throughout the simulations to allow slug size design to be optimized. An investigation on how mixing impacts the optimal concentration of both polymer and surfactant in each slug would be extremely valuable.

2. The salinity of the injected chemicals and reservoir were held constant across simulation in this study. Changing this design and analyzing the salinity scheme with dispersion effects would help to further explain these results.

3. A study on each parameter known to impact dispersion as found by Garmeh and Johns (2010) would highlight more of the differences in mixing effects between chemical and miscible gas floods.

4. An expansion of our study on the dispersivity contribution from permeability. The one-dimensional convection dispersion equation was used, and we were limited to ten thousand grid-blocks. Increasing the number of grid-blocks and updating the equations used to estimate dispersivity would improve the estimation and reduce any error.

5. Comparison of the extrapolated value of physical dispersivity to other known measures of testing this value would indicate the quality of this assumption and methodology.

6. Expand analysis on the use of a fluid dispersivity factor to alter simulated mixing and how this relates to mobility ratio and each individual chemical.
7. The grid-block optimization accounting for dispersion should consider the fluids of interest, not only the single-phase tracer. The optimization should be expanded to focus on the fluid most sensitive to mixing, to match the simulated dispersion to physical values.
### Nomenclature

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASP</td>
<td>Alkali-surfactant-polymer</td>
</tr>
<tr>
<td>Capex</td>
<td>Capital expenditures</td>
</tr>
<tr>
<td>CDE</td>
<td>Convection dispersion equation</td>
</tr>
<tr>
<td>CMC</td>
<td>Critical micelle concentration</td>
</tr>
<tr>
<td>EOR</td>
<td>Enhanced oil recovery</td>
</tr>
<tr>
<td>HPAM</td>
<td>Partially hydrolyzed polyacrylamide</td>
</tr>
<tr>
<td>IFT</td>
<td>Interfacial tension</td>
</tr>
<tr>
<td>IOR</td>
<td>Incremental oil recovery</td>
</tr>
<tr>
<td>IPV</td>
<td>Inaccessible pore volume</td>
</tr>
<tr>
<td>MENP</td>
<td>Minimum economic number of patterns</td>
</tr>
<tr>
<td>meq</td>
<td>Milliequivalents, number of ions in a solution</td>
</tr>
<tr>
<td>MME</td>
<td>Minimum miscibility enrichment</td>
</tr>
<tr>
<td>MMP</td>
<td>Minimum miscibility pressure</td>
</tr>
<tr>
<td>MRNP</td>
<td>Minimum robust number of patterns</td>
</tr>
<tr>
<td>NPV</td>
<td>Net present value</td>
</tr>
<tr>
<td>OOIP</td>
<td>Original oil in place</td>
</tr>
<tr>
<td>Opex</td>
<td>Operational expenditures</td>
</tr>
<tr>
<td>PVI</td>
<td>Pore volumes injected</td>
</tr>
<tr>
<td>SP</td>
<td>Surfactant-polymer</td>
</tr>
<tr>
<td>STB</td>
<td>Volume of oil in barrels at standard conditions</td>
</tr>
<tr>
<td>TVD</td>
<td>Total-variation diminishing</td>
</tr>
<tr>
<td>UF</td>
<td>Utility factor, lb. of chemical/ STB of incremental oil</td>
</tr>
<tr>
<td>UTCHEM</td>
<td>University of Texas Chemical Flooding Simulator</td>
</tr>
</tbody>
</table>
**Equation Symbols**

- \( a \): Radius of a capillary tube
- \( A_H \): Empirical Hand parameter for phase behavior calculation
- \( B_H \): Empirical Hand parameter for phase behavior calculation
- \( C \): Concentration
- \( C_D \): Dimensionless concentration, normalized between injection and initial conditions
- \( C_I \): Initial concentration
- \( C_{ij} \): Concentration of component \( i \) in phase \( j \)
- \( C_J \): Injection concentration
- \( C_{SEU} \): Upper effective salinity limit for Type III phase region
- \( C_{SEL} \): Lower effective salinity limit for Type III phase region
- \( D_0 \): Diffusion coefficient
- \( d_p \): Average particle diameter
- \( E_A \): Areal sweep efficiency
- \( E_D \): Displacement efficiency
- \( E_R \): Recovery efficiency
- \( E_V \): Volumetric sweep efficiency
- \( E_Z \): Vertical sweep efficiency
- \( F \): Formation electrical resistivity factor
- \( g \): Gravitational constant
- \( H \): Height of the reservoir, ft.
- \( H.O.T. \): Higher order terms, additional error truncated from finite difference solution
- \( J \): Diffusive flux
- \( k \): Permeability, md
- \( \bar{K}_{ij} \): Diffusion/dispersion tensor
- \( K_i \): Longitudinal dispersion coefficient
- \( k_r \): Relative permeability
- \( L \): Length of the reservoir, ft.
- \( M \): Mobility ratio
$N_B$  Bond Number

$N_c$  Number of components

$N_G$  Gravity number

$N_p$  Number of phases

$N_{Pe}$  Peclet number

$N_T$  Trapping number

$N_{vc}$  Capillary number

$Q$  Maximum rate injected or produced from each well-block

$R_{ij}$  Mass generation of component $i$ in phase $j$ through chemical and biological reaction

$R_L$  Effective aspect ratio

$S^*$  Optimal effective salinity, meq/ml.

$t_D$  Dimensionless time, pore volumes injected

$u$  Interstitial fluid velocity

$v$  Average fluid velocity

$V_{DP}$  Dykstra-Parsons coefficient

$x, y, z$  Cartesian directions

$x_D$  Dimensionless distance in the $x$-direction

$\phi$  Porosity

$\hat{\lambda}_x$  Permeability correlation length in the $x$-direction

$\hat{\lambda}_z$  Permeability correlation length in the $z$-direction

$\sigma$  Interfacial tension

$\alpha_{Permeability}$  Dispersivity contribution of the permeability distribution

$\alpha_{Physical}$  Dispersivity representative of the physical reservoir

$\alpha_l$  Longitudinal dispersivity

$\alpha_n$  Numerical dispersion

$\alpha_{Reservoir}$  Dispersivity of the reservoir

$\alpha_{Total}$  Total dispersivity from all sources

$\beta$  Chemical cost factor, cost of chemical/lb. relative to cost of polymer per lb. polymer

$\varepsilon_j$  Volume fraction of phase $j$
\( \mu \)  
Viscosity, cp

\( \rho_j \)  
Density of phase  \( j \)

\( \omega_{ij} \)  
Mass fraction of component  \( i \) in phase  \( j \)
References


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Appendices

Appendix A: Derivation of the Convection Dispersion Equation from Material Balance

The convection dispersion equation is a specific solution of the general compositional equations solved through the material balance of a component, $i$, in phase $j$. Taking an arbitrary volume, this material balance is:

$$
\left( \text{Rate of accumulation of } i \text{ in phase } j \text{ in } V \right) = \left( \text{Net rate of } i \text{ in phase } j \text{ transported into } V \right) + \left( \text{Net rate of generation of } i \text{ in } j \text{ inside of } V \right)
$$

(A.1)

These are the accumulation, flux, and source terms respectively, from left to right.

The overall compositional equation can be derived using the following definitions (Lake et al. 2014):

$$
\rho_j = \text{Phase density} = \frac{\text{Total mass of phase } j}{\text{Volume of phase } j}
$$

(A.2)

$$
\omega_j = \text{Mass fraction of } i \text{ in } j = \frac{\text{Mass of } i \text{ in phase } j}{\text{Total mass of phase } j}
$$

(A.3)

$$
\varepsilon_j = \text{Volume fraction of phase } j = \frac{\text{Volume of phase } j}{\text{Bulk volume}}
$$

(A.4)

$$
\overline{K}_j = \text{Diffusion/dispersion tensor}
$$

(A.5)

$$
R_j = \text{Mass generation of } i \text{ in } j \text{ through chemical and biological reactions}
$$

(A.6)

The overall compositional equation simplifies, when summed across all $N_p$ phases.

$$
\frac{\partial}{\partial t} \sum_{j=1}^{N_p} \rho_j \omega_j \varepsilon_j + \nabla \cdot \left( \sum_{j=1}^{N_p} \rho_j \omega_j u_j \right) - \nabla \cdot \left( \sum_{j=1}^{N_p} \varepsilon_j \overline{K}_j \right) + \nabla \cdot \left( \rho_j \omega_j \right) - \sum_{j=1}^{N_p} R_j = 0
$$

(A.7)

From this equation, we make the following assumptions:
1. \( N_p = 2 \), one flowing and one solid phase.

2. No chemical processes, \( R_{ij} = 0 \).

3. No adsorption, \( \omega = 0 \).

4. Darcy’s Law applies, \( \vec{u} = \frac{k}{\mu} (\vec{\nabla}P + \rho g) \), where \( \vec{u} \) is the interstitial velocity, \( k \) the permeability tensor, \( \mu \) the viscosity, \( \vec{\nabla}P \) the pressure gradient, and \( g \) the gravitational constant.

These assumptions result in the following equation, used in many commercial applications for first contact miscible (FMC) floods.

\[
\frac{\partial}{\partial t} (\phi \rho \omega) + \vec{\nabla} \cdot (\rho \omega \vec{u}) - \vec{\nabla} \cdot \left[ \phi K_{ii} \vec{\nabla} \rho \omega \right] = 0 \tag{A.8}
\]

From Equation A.8, we make the following assumptions:

1. 1D flow in the \( x \) direction

2. \( \phi \) is constant spatially and with time

3. \( \vec{u} \) is constant spatially

4. \( K_{ii} \) is constant spatially and with time

5. \( N_c = 2 \) with a water and a tracer, where \( \rho \) is constant

6. Ideal mixing

7. Temperature and pressure are fixed

We then define the component concentration \( C_i \),

\[
C_i = \frac{\rho \omega_i}{\rho_i} \tag{A.9}
\]

This results in the convection dispersion equation for each component:
As is often done, the component subscripts, $i$, are dropped in Equation 2.5.

\[
\phi \frac{\partial C_i}{\partial t} + u \frac{\partial C_i}{\partial x} - \phi K_i \frac{\partial^2 C_i}{\partial x^2} = 0
\]  

(A.10)
Appendix B: Hand’s Model

The microemulsion phase behavior used in this study and in this version of UTCHEM is Hand’s Model (Hand 1939). This is based on the observation that the equilibrium phase concentrations create straight lines with a log-log scale in a Hand plot. We define the concentration of each component in each phase, using the three pseudocomponents of surfactant, oil and brine. \( C_{ij} \) denotes the concentration of component \( i \) in phase \( j \). Figure B.1 shows the Hand plot for a Type II- phase diagram.

\[
\begin{align*}
C_{3j} &= A_H \left( \frac{C_{3j}}{C_j} \right)^{B_H} \\
&= 1, 2, 3
\end{align*}
\]

Figure B.1 – Correspondence between (a.) ternary and (b.) Hand plot. Adapted from UTCHEM (2000).

This plot shows the linear relationship identified by Hand. Hand’s equation is valid only if these straight lines are present, and relies on experimental measurements over a tested range of values,

where \( A_H \) and \( B_H \) are empirical parameters. In UTCHEM the inputs for microemulsion phase behavior are \( C_{33\text{max}0} \), \( C_{33\text{max}1} \), and \( C_{33\text{max}2} \) (UTCHEM 2000). These inputs are used to calculate values of \( A_{H0} \), \( A_{H1} \), and \( A_{H2} \) using equation B.2 (Sheng 2011).
\[ C_{33\text{max}} = \frac{\sqrt{A_H}}{2 + \sqrt{A_H}} \]  

(B.2)

A detailed analysis of determining these parameters for a UTCHEM model can be found in the Technical Document for UTCHEM (UTCHEM 2000) and presented by Sheng (2011).
Appendix C: Sample UTCHEM Input Files

The following files are examples of the input files used in this study. All studies used the University of Texas Chemical Numerical Simulator (UTCHEM). The reservoir model is two-dimensional, containing two wells, injected with constant rate and produced with constant pressure. From both INPUT files, the permeability distribution has been excluded for brevity. These are available upon request to the department of Energy and Mineral Engineering at The Pennsylvania State University.

The following HEAD and INPUT files were used in the single-phase tracer simulations to estimate dispersivity from a permeability distribution. This case represents the reservoir specifically designed for this process, with an entirely water saturated reservoir.

HEAD

utex01
NX NY NZ N NWELL
64 1 32 9 2
NTW NTA
1 0
NO NPHAS
0 3
NSUB MSUB
0 0

INPUT

************************************************************************................................................................................................................
CC BRIEF DESCRIPTION OF DATA SET : UTCHEM (VERSION 9.0 ) *
CC************************************************************************................................................................................................................
CC PERMEABILITY DRIVEN DISPERSIVITY 64X1X32 *
CC************************************************************************................................................................................................................
CC LENGTH (FT) : 320 PROCESS : SINGLE PHASE TRACER *
CC THICKNESS (FT) : 32 INJ. RATE (FT3/DAY) : 100 *
CC WIDTH (FT) : 32 COORDINATES : CARTESIAN *
CC POROSITY : 0.20 *
CC GRID BLOCKS : 64X1X32 *
CC DATE : 12/21/2017 *
CC************************************************************************................................................................................................................
CC RESERVOIR DESCRIPTION *
CC************************************************************************................................................................................................................
RUNNO

PD1
CC
CC

--- HEADER

PD1
TESTING UTCHEM VERSION 9 ON DEC 500au (MARATHON)
SURFACTANT/POLYMER, SALINITY GRADIENT RUN (.4 -> .3 -> .1).
CC
CC
CC

SIMULATION FLAGS

--- IMODE IMES IDISPC ICWM ICAP IREACT IBIO ICOORD ITREAC ITC IGAS IENG

CC
CC
NO. OF GRID BLOCKS, FLAG SPECIFIES CONSTANT OR VARIABLE GRID SIZE, UNIT

--- NX NY NZ IDXZ IUNIT

CC
CC
CONSTANT GRID BLOCK SIZE IN X, Y, AND Z

--- DX1 DY1 DZ1

CC
CC
TOTAL NO. OF COMPONENTS, NO. OF TRACERS, NO. OF GEL COMPONENTS

--- N NO NTW NTA NGC NG NOTH

CC
CC
NAME OF SPECIES

--- SPNAME(I) FOR I=1,N

WATER
OIL
SURF.
POLYMER
ANION
CALCIUM
ALCOHOL
GAS(NO)
TRACER
CC
CC
FLAG INDICATING IF THE COMPONENT IS INCLUDED IN CALCULATIONS OR NOT

--- ICF(KC) FOR KC=1,N

CC
CC
******************************************************************
CC
CC    OUTPUT OPTIONS

******************************************************************
CC
CC
FLAG FOR PV OR DAYS TO PRINT OR TO STOP THE RUN

--- ICUMTM ISTOP IOUTGMS

CC
CC
FLAG INDICATING IF THE PROFILE OF KCTH COMPONENT SHOULD BE WRITTEN

--- IPRFLG(KC),KC=1,N

CC
CC
FLAG FOR individual map files

--- IPPRES IPSAT IPCTOT IPBIO IPCAP IPGEL IPALK IPTEMP IPOBS

CC
CC
FLAG for individual output map files

--- ICKL IVIS IPER ICNM ICSE ihystp ifoamp inoneq

CC
CC
FLAG for variables to PROF output file

--- Iads IVel Irkf Iphse

CC
CC
******************************************************************
CC
CC    RESERVOIR PROPERTIES

CC
CC
******************************************************************

CC MAX. SIMULATION TIME (DAYS)
*----- TMAX
  10.0
CC ROCK COMPRESSIBILITY (1/PSI), STAND. PRESSURE(PSIA)
*----- COMPR  PSTAND
  0   14.7
CC FLAGS INDICATING CONSTANT OR VARIABLE POROSITY, X,Y,AND Z PERMEABILITY
*----- IPOR1 IPERMX IPERMY IPERMZ IMOD
  0  2  3  3  0
CC CONSTANT POROSITY
*----- PORC1
  .20
CC CONSTANT X-PERMEABILITY (MILIDARCY) FOR LAYER K = 1,NZ
*----- PERMXC

[EXCLUDED PERMEABILITY DISTRIBUTION]
CC CONSTANT Y-PERMEABILITY (MILIDARCY) FOR LAYER K = 1,NZ
*----- PERMYC
  1.
CC CONSTANT Z-PERMEABILITY (MILIDARCY)
*----- PERMZC
  0.1
CC FLAG FOR CONSTANT OR VARIABLE DEPTH, PRESSURE, WATER SATURATION
*----- IDEPTH IPRESS ISWI ICWI
  0  0  0  -1
CC CONSTANT DEPTH (FT)
*----- D111
  1000.0
CC CONSTANT PRESSURE (PSIA)
*----- PRESS1
  1000.0
CC CONSTANT INITIAL WATER SATURATION
*----- SWI
  1.0
cc
*--- c50  c60
  0.  0.
cc
CC OIL CONC. AT PLAIT POINT FOR TYPE II(+)AND TYPE II(-), CMC
*----- C2PLC C2PRC EPSME IHAND
  0  1  .0001  0
CC FLAG INDICATING TYPE OF PHASE BEHAVIOR PARAMETERS
*----- IFGHBN
  0
CC SLOPE AND INTERCEPT OF BINODAL CURVE AT ZERO, OPT., AND 2XOPT SALINITY
CC FOR ALCOHOL 1
*----- HBNS70 HBNC70 HBNS71 HBNC71 HBNS72 HBNC72
  0.131  0.1  0.191  0.026  0.363  0.028
CC SLOPE AND INTERCEPT OF BINODAL CURVE AT ZERO, OPT., AND 2XOPT SALINITY
CC FOR ALCOHOL 2
*----HBNS80 HBNC80 HBNS81 HBNC81 HBNS82 HBNC82
  0. 0. 0. 0. 0. 0.
CC
CC LOWER AND UPPER EFFECTIVE SALINITY FOR ALCOHOL 1 AND ALCOHOL 2
*----CSEL7 CSEU7 CSEL8 CSEU8
   0.177  0.344  0. 0.
CC
CC THE CSE SLOPE PARAMETER FOR CALCIUM AND ALCOHOL 1 AND ALCOHOL 2
*----BETA6 BETA7 BETA8
   0.8 -2. 0.
CC
CC FLAG FOR ALCOHOL PART. MODEL AND PARTITION COEFFICIENTS
*----IALC OPSK7O OPSK7S OPSK8O OPSK8S
   1 0. 0. 0. 0.
CC
CC NO. OF ITERATIONS, AND TOLERANCE
*----NMAX EPSALC
   20 .0001
CC
CC ALCOHOL 1 PARTITIONING PARAMETERS IF IALC=1
*----AKWC7 AKWS7 AKM7 AK7 PT7
   4.671  1.79  48. 35.31 .222
CC
CC ALCOHOL 2 PARTITIONING PARAMETERS IF IALC=1
*----AKWC8 AKWS8 AKM8 AK8 PT8
   0. 0. 0. 0. 0.
CC
CC
*---- IFT MODEL FLAG
   0
CC
CC INTERFACIAL TENSION PARAMETERS
*----G11 G12 G13 G21 G22 G23
  13. -14.8 .007 13. -14.5 .010
CC
CC LOG10 OF OIL/WATER INTERFACIAL TENSION
*----XIFTW
   1.3
CC
CC MASS TRANSFER FLAG
*----IMASS icor
   0 0
CC
CC CAPILLARY DESATURATION PARAMETERS FOR PHASE 1, 2, AND 3
*----ITRAP T11 T22 T33
   1 1865.  59074  364.2
CC
CC RELATIVE PERM. FLAG (0:IMBIBITION COREY,1:FIRST DRAINAGE COREY)
*----IPERM
   0
CC
CC FLAG FOR CONSTANT OR VARIABLE REL. PERM. PARAMETERS
*----ISRW IPRW IEW
   0 0 0
CC
CC CONSTANT RES. SATURATION OF PHASES 1,2,AND 3 AT LOW CAPILLARY NO.
*----S1RWC S2RWC S3RWC
  .00001 .00001 .00001
CC
CC CONSTANT ENDPOINT REL. PERM. OF PHASES 1,2,AND 3 AT LOW CAPILLARY NO.
*----P1RW P2RW P3RW
   1.  1.  1.
CC
CC CONSTANT REL. PERM. EXPONENT OF PHASES 1,2,AND 3 AT LOW CAPILLARY NO.
*----E1W E2W E3W
   2.  2.  2.
CC
CC RES. SATURATION OF PHASES 1,2,AND 3 AT HIGH CAPILLARY NO.
*----S1RC S2RC S3RC
   .0  .0  .0
CC
CC ENDPOINT REL. PERM. OF PHASES 1, 2, AND 3 AT HIGH CAPILLARY NO.
*----- PIRC  P2RC  P3RC
   1.  1.  1.
CC
CC REL. PERM. EXPONENT OF PHASES 1, 2, AND 3 AT HIGH CAPILLARY NO.
*-----E13C  E23C  E31C
   2.  2.  2.
CC
CC WATER AND OIL VISCOSITY, RESERVOIR TEMPERATURE
*----- VIS1  VIS2  TSTAND
   1.  1.  0.
CC
CC VISCOSITY PARAMETERS
*----- ALPHAL  ALPHAL2  ALPHAL3  ALPHA4  ALPHA5
   4.  5.  0.  0.9  0.7
CC
CC PARAMETERS TO CALCULATE POLYMER VISCOSITY AT ZERO SHEAR RATE
*----- AP1  AP2  AP3
   0.  0.  0.
CC
CC PARAMETER TO COMPUTE CSEP, MIN. CSEP, AND SLOPE OF LOG VIS. VS. LOG CSEP
*----- BETA  CSE1  SSLOPE
   10. .01  0.0
CC
CC PARAMETER FOR SHEAR RATE DEPENDENCE OF POLYMER VISCOSITY
*----- GAMMAC  GAMHF  POWN
    0.  13.  1.645
CC
CC FLAG FOR POLYMER PARTITIONING, PERM. REDUCTION PARAMETERS
*----- IPOLYM EPHI1  EPHI4  BRK  CRK
    0  1.  1.  0.  0.0
CC
CC SPECIFIC WEIGHT FOR COMPONENTS 1, 2, 3, 7, AND 8, AND GRAVITY FLAG
*----- DEN1  DEN2  DEN3  DEN7  DEN8  DEN13  DEN14  DEN17  DEN18
    .4291  .3491  .4391  .42  .346  0.  1
CC
CC FLAG FOR CHOICE OF UNITS ( 0: BOTTOMHOLE CONDITION, 1: STOCK TANK)
*----- ISTB
    0
CC
CC COMPRESSIBILITY FOR VOL. OCCUPYING COMPONENTS 1, 2, 3, 7, AND 8
*----- COMPC(1)  COMPC(2)  COMPC(3)  COMPC(7)  COMPC(8)
    0.  0.  0.  0.  0.
CC
CC CONSTANT OR VARIABLE PC PARAM., WATER-WET OR OIL-WET PC CURVE FLAG
*----- ICPC  IEPC  IOC
    0  0  0
CC
CC CAPILLARY PRESSURE PARAMETER, CPC0
*----- CPC0
    0.
CC
CC CAPILLARY PRESSURE PARAMETER, EPC0
*----- EPC0
    2.
CC
CC MOLECULAR DIFFUSION COEF. KCTH COMPONENT IN PHASE 1 (D(KC), KC=1, N)
    0.  0.  0.  0.  0.  0.  0.  0.  0.
CC
CC MOLECULAR DIFFUSION COEF. OF KCTH COMPONENT IN PHASE 2 (D(KC), KC=1, N)
    0.  0.  0.  0.  0.  0.  0.  0.  0.
CC
CC MOLECULAR DIFFUSION COEF. OF KCTH COMPONENT IN PHASE 3 (D(KC), KC=1, N)
    0.  0.  0.  0.  0.  0.  0.  0.  0.
CC
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 1
*----- ALPHAL(1)  ALPHAT(1)
    0.  .0
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 2
*----ALPHAL(2)  ALPHAT(2)
     0.     0.
CC
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 3
*----ALPHAL(3)  ALPHAT(3)
     0.     0.
CC
CC FLAG TO SPECIFY ORGANIC ADSORPTION CALCULATION
*----IADSO
     0
CC
CC SURFACANT AND POLYMER ADSORPTION PARAMETERS
*----AD31  AD32  B3D  AD41  AD42  B4D  IADK, IADS1, FADS REFK,md
     0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  500
CC
CC PARAMETERS FOR CATION EXCHANGE OF CLAY AND SURFACANT
*----QV  XKC  XKS  EQW
     0.   0.   0.   0.
CC
*** tk
     0
CC
*** tks  c5ini
     0.  0.0
CC
*** rdc
     0
CC
*** ret
     0
CC
CC*******************************************************************
CC                                                                  *
CC    WELL DATA                                                     *
CC*******************************************************************
CC
CC FLAG FOR RIGHT AND LEFT BOUNDARY
*---- IBOUND izone
     0  0
CC
CC TOTAL NUMBER OF WELLS, WELL RADIUS FLAG, FLAG FOR TIME OR COURANT NO.
*----NWELL  IRO  ITSTEP  NWREL
     2  2  0  2
CC
CC WELL ID,LOCATIONS, AND FLAG FOR SPECIFYING WELL TYPE, WELL RADIUS, SKIN
*----IDW  IW  JW  IFLAG  RW  SWELL  IDIR  IFIRST  ILAST  IPRF
     1  1  1  1  0.25  0.  3  1  32  0
CC
CC WELL NAME
*---- WELNAM
INJECTOR
CC
CC ICHEK, MAX. AND MIN. ALLOWABLE BOTTOMHOLE PRESSURE AND RATE
*----ICHEK PWFMIN  PWFMAX  QTMIN  QTMAX
     0  0.0  5000.  0.0  50000.
CC
CC WELL ID, LOCATION, AND FLAG FOR SPECIFYING WELL TYPE, WELL RADIUS, SKIN
*----IDW  IW  JW  IFLAG  RW  SWELL  IDIR  IFIRST  ILAST  IPRF
     2  64  1  2  0.25  0.  3  1  32  0
CC
CC WELL NAME
*---- WELNAM
PRODUCER
CC
CC ICHEK, MAX. AND MIN. ALLOWABLE BOTTOMHOLE PRESSURE AND RATE
For the surfactant-polymer study, the following HEAD and INPUT files were used, representing the case of $V_{DP} = 0.40$, $S^* = 0.36$ meq/ml., $\alpha_{input} = 0.0$ ft., and with the design of an SP slug of 0.10 PV, and a polymer buffer of 0.10 PV.

HEAD

utex01
NX NY NZ N NWELL
64 1 32 8 2
NTW NTA 0
NO NPHAS 0 3
NSUB MSUB 0 0

INPUT

CC*******************************************************************
CC BRIEF DESCRIPTION OF DATA SET : UTCHEM (VERSION 9.0 ) *
CC*******************************************************************
CC SURFACANT/POLYMER FLOOD TEST (EX01), 64X1X32 *
CC LENGTH (FT) : 320 PROCESS : SURFACANT/POLYMER *
CC THICKNESS (FT) : 32 INJ. RATE (FT3/DAY) : 100 *
CC WIDTH (FT) : 32 COORDINATES : CARTESIAN *
CC POROSITY : 0.20 *
CC GRID BLOCKS : 64X1X32 *
CC DATE : 01/22/2017 *
CC *
CC*******************************************************************
CC*******************************************************************
**RESERVOIR DESCRIPTION**

**SIMULATION FLAGS**

**GRIDBLOCKS, FLAG SPECIFIES CONSTANT OR VARIABLE GRID SIZE, UNIT**

**COMPONENTS, NO. OF TRACERS, NO. OF GEL COMPONENTS**

**NAME OF SPECIES**

**PROFILE OF KCTH COMPONENT SHOULD BE WRITTEN**

**FLAG FOR INDIVIDUAL MAP FILES**

**FLAG FOR VARIABLES TO PROF OUTPUT FILE**

---

**EX01**

**DIFFUSIVITY**

**OUTPUT OPTIONS**

---

**RUNNO**

**EX01**

**HEADER**

**SURFACTANT/POLYMER, SALINITY GRADIENT RUN (.4 -> .3 -> .1).**

---

**NO. OF GRIDBLOCKS, FLAG SPECIFIES CONSTANT OR VARIABLE GRID SIZE, UNIT**

**TOTAL NO. OF COMPONENTS, NO. OF TRACERS, NO. OF GEL COMPONENTS**

**NAME OF SPECIES**

**FLAG INDICATING IF THE COMPONENT IS INCLUDED IN CALCULATIONS OR NOT**

**FLAG FOR PV OR DAYS TO PRINT OR TO STOP THE RUN**

**FLAG FOR INDIVIDUAL MAP FILES**

**FLAG FOR VARIABLES TO PROF OUTPUT FILE**

---

147
**RESERVOIR PROPERTIES**

MAX. SIMULATION TIME (DAYS)

```
  TMAX
  10.03
```

ROCK COMPRESSIBILITY (1/PSI), STAND. PRESSURE(PSIA)

```
  COMPR  PSTAND
  0.     0.
```

FLAGS INDICATING CONSTANT OR VARIABLE POROSITY, X,Y,AND Z PERMEABILITY

```
  IPOR1  IPERMX  IPERMY  IPERMZ  IMOD
  0   2     3      3      0
```

CONSTANT POROSITY

```
  PORC1
  .20
```

CONSTANT X-PERMEABILITY (MILIDARCY) FOR LAYER K = 1,NZ

```
  PERMXC
  [EXCLUDED PERMEABILITY DISTRIBUTION]
```

CONSTANT Y-PERMEABILITY (MILIDARCY) FOR LAYER K = 1,NZ

```
  PERMYC
  1.0
```

CONSTANT Z-PERMEABILITY (MILIDARCY)

```
  PERMZC
  0.1
```

FLAG FOR CONSTANT OR VARIABLE DEPTH, PRESSURE, WATER SATURATION

```
  IDEPTH  IPRESS  ISWI  ICWI
  0      0       0    -1
```

CONSTANT DEPTH (FT)

```
  D111
  1000.
```

CONSTANT PRESSURE (PSIA)

```
  PRESS1
  1000.
```

CONSTANT INITIAL WATER SATURATION

```
  SWI
  .5
```

```
  c50   c60
  0.4   0.003
```

**PHYSICAL PROPERTY DATA**

OIL CONC. AT PLAIT POINT FOR TYPE II(+)AND TYPE II(-), CMC

```
  C2PLC  C2PRC  EPSME  IHAND
  0.     1.     .001   0
```

FLAG INDICATING TYPE OF PHASE BEHAVIOR PARAMETERS
*------ IFGHB
CC SLOPE AND INTERCEPT OF BINODAL CURVE AT ZERO, OPT., AND 2XOPT SALINITY
CC FOR ALCOHOL 1
*------HBN570 HBNC70 HBNS71 HBNC71 HBNS72 HBNC72
 0.131 0.061 0.191 0.037 0.263 0.056
CC SLOPE AND INTERCEPT OF BINODAL CURVE AT ZERO, OPT., AND 2XOPT SALINITY
CC FOR ALCOHOL 2
*------HBN580 HBNC80 HBNS81 HBNC81 HBNS82 HBNC82
 0.  0.  0.  0.  0.  0.
CC
CC LOWER AND UPPER EFFECTIVE SALINITY FOR ALCOHOL 1 AND ALCOHOL 2
*------CSEL7 CSEU7 CSEL8 CSEU8
 0.32 0.40 0.  0.
CC
CC THE CSE SLOPE PARAMETER FOR CALCIUM AND ALCOHOL 1 AND ALCOHOL 2
*------BETA6 BETA7 BETA8
 0.8  -2.  0.
CC
CC FLAG FOR ALCOHOL PART. MODEL AND PARTITION COEFFICIENTS
*------IALC OPSK70 OPSK75 OPSK80 OPSK85
 1  0.  0.  0.  0.
CC
CC NO. OF ITERATIONS, AND TOLERANCE
*------NALMAX EPSALC
 50   .0001
CC
CC ALCOHOL 1 PARTITIONING PARAMETERS IF IALC=1
*------AKWC7 AKWS7 AKM7 AK7 PT7
 4.671 1.79 48. 35.31 .222
CC
CC ALCOHOL 2 PARTITIONING PARAMETERS IF IALC=1
*------AKWC8 AKWS8 AKM8 AK8 PT8
 0.  0.  0.  0.  0.
CC
CC
*------ IFT MODEL FLAG
 0
CC
CC INTERFACIAL TENSION PARAMETERS
*------G11 G12 G13 G21 G22 G23
 13. -14.8 .007 13. -14.5 .010
CC
CC LOG10 OF OIL/WATER INTERFACIAL TENSION
*------XIFTW
 1.3
CC
CC MASS TRANSFER FLAG
*------IMASS icor
 0  0
CC
CC CAPILLARY DESATURATION PARAMETERS FOR PHASE 1, 2, AND 3
*------ITRAP T11 T22 T33
 1 1865. 59074 364.2
CC
CC RELATIVE PERM. FLAG (0:IMBIBITION COREY,1:FIRST DRAINAGE COREY)
*------IPERM
 0
CC
CC FLAG FOR CONSTANT OR VARIABLE REL. PERM. PARAMETERS
*------ISRW IPRW IEW
 0  0  0
CC
CC CONSTANT RES. SATURATION OF PHASES 1, 2, AND 3 AT LOW CAPILLARY NO.
*------S1RWC S2RWC S3RWC
 .31  .3  .31
CC
CC CONSTANT ENDPOINT REL. PERM. OF PHASES 1, 2, AND 3 AT LOW CAPILLARY NO.
*------P1RW P2RW P3RW
 .11  0.95  .11
CC
CC CONSTANT REL. PERM. EXPONENT OF PHASES 1, 2, AND 3 AT LOW CAPILLARY NO.
**E1W**  **E2W**  **E3W**

1.1  2.0  1.1

**RES. SATURATION OF PHASES 1,2, AND 3 AT HIGH CAPILLARY NO.**

**S1RC**  **S2RC**  **S3RC**

0.0  0.0  0.0

**ENDPOINT REL. PERM. OF PHASES 1,2, AND 3 AT HIGH CAPILLARY NO.**

**P1RC**  **P2RC**  **P3RC**

1.0  1.0  1.0

**REL. PERM. EXPONENT OF PHASES 1,2, AND 3 AT HIGH CAPILLARY NO.**

**E13C**  **E23C**  **E31C**

1.0  2.0  1.0

**WATER AND OIL VISCOSITY, RESERVOIR TEMPERATURE**

**VIS1**  **VIS2**  **TSTAND**

1.0  15.0  77.0

**VISCOSITY PARAMETERS**

**ALPHA1**  **ALPHA2**  **ALPHA3**  **ALPHA4**  **ALPHA5**

1.7  2.0  6.0  0.8  0.8

**PARAMETERS TO CALCULATE POLYMER VISCOSITY AT ZERO SHEAR RATE**

**AP1**  **AP2**  **AP3**

71.473  2700.0  1930.083

**PARAMETER TO COMPUTE CSEP, MIN. CSEP, AND SLOPE OF LOG VIS. VS. LOG CSEP**

**BETAP**  **CSEP1**  **SSLOPE**

10.0  0.01  0.17

**PARAMETER FOR SHEAR RATE DEPENDENCE OF POLYMER VISCOSITY**

**GAMMAC**  **GAMHF**  **POWN**

20.0  12.86  1.8

**FLAG FOR POLYMER PARTITIONING, PERM. REDUCTION PARAMETERS**

**IPOLYM**  **EPHI3**  **EPHI4**  **BRK**  **CRK**

1.0  1.0  0.8  0.0186

**SPECIFIC WEIGHT FOR COMPONENTS 1, 2, 3, 7, AND 8, AND GRAVITY FLAG**

**DEN1**  **DEN2**  **DEN23**  **DEN3**  **DEN7**  **DEN8**  **IDEN**

0.433  0.368  0.368  0.42  0.346  0.0  2

**FLAG FOR CHOICE OF UNITS (0: BOTTOMHOLE CONDITION, 1: STOCK TANK)**

**ISTB**

0

**COMPRESSIBILITY FOR VOL. OCCUPYING COMPONENTS 1, 2, 3, 7, AND 8**

**COMPC(1)**  **COMPC(2)**  **COMPC(3)**  **COMPC(7)**  **COMPC(8)**

0.0  0.0  0.0  0.0  0.0

**CONSTANT OR VARIABLE PC PARAM., WATER-WET OR OIL-WET PC CURVE FLAG**

**ICPC**  **IEPC**  **IOW**

0  0  0

**CAPILLARY PRESSURE PARAMETER, CPC0**

**CPC0**

9.0

**CAPILLARY PRESSURE PARAMETER, EPC0**

**EPC0**

2.0

**MOLECULAR DIFFUSION COEF. KCTH COMPONENT IN PHASE 1 (D(KC), KC=1, N)**

**D(1)**  **D(2)**  **D(3)**  **D(4)**  **D(5)**  **D(6)**  **D(7)**  **D(8)**

0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

**MOLECULAR DIFFUSION COEF. OF KCTH COMPONENT IN PHASE 2 (D(KC), KC=1, N)**

**D(1)**  **D(2)**  **D(3)**  **D(4)**  **D(5)**  **D(6)**  **D(7)**  **D(8)**

0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

**MOLECULAR DIFFUSION COEF. OF KCTH COMPONENT IN PHASE 3 (D(KC), KC=1, N)**
  0.  0.  0.  0.  0.  0.  0.  0.  
CC
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 1
*-----ALPHAL(1)       ALPHAT(1)
  0.  .0 
CC
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 2
*-----ALPHAL(2)       ALPHAT(2)
  0.  0. 
CC
CC LONGITUDINAL AND TRANSVERSE DISPERSIVITY OF PHASE 3
*-----ALPHAL(3)       ALPHAT(3)
  0.  .0 
CC
CC FLAG TO SPECIFY ORGANIC ADSORPTION CALCULATION
*-----IADSO
  0 
CC
CC SURFACTANT AND POLYMER ADSORPTION PARAMETERS
*-----AD31  AD32  B3D  AD41  AD42  B4D  IADK, IADS1, FADS REFK,md
  0.  0.  0.  0.  0.  0.  0.  0.  500 
CC
CC PARAMETERS FOR CATION EXCHANGE OF CLAY AND SURFACTANT
*-----QV     XKC     XKS    EQW 
  0.  0.  0.  0.  
CC
CC*******************************************************************
CC                                                                  *
CC    WELL DATA
CC*******************************************************************
CC
CC FLAG FOR RIGHT AND LEFT BOUNDARY
*----- IBOUND izone
  0 0 
CC
CC TOTAL NUMBER OF WELLS, WELL RADIUS FLAG, FLAG FOR TIME OR COURANT NO.
*-----NWELL   IRO   ITSTEP  NWREL
  2  2  1  2 
CC
CC WELL ID,LOCATIONS,AND FLAG FOR SPECIFYING WELL TYPE, WELL RADIUS, SKIN
*-----IDW   IW   JW   IFLAG    RW    SWELL  IDIR   IFIRST   ILAST  IPRF
  1  1  1  1   0.25  0.  3  1  32  0 
CC
CC WELL NAME
*----- WELNAM 
INJECTOR 
CC
CC ICHECK, MAX. AND MIN. ALLOWABLE BOTTOMHOLE PRESSURE AND RATE
*-----ICHECK PWFMIN  PWFMAX  QTMIN  QTMAX
  2  0.0  100000.  0.0  100000. 
CC
CC WELL ID, LOCATION, AND FLAG FOR SPECIFYING WELL TYPE, WELL RADIUS, SKIN
*-----IDW   IW   JW   IFLAG    RW    SWELL  IDIR   IFIRST   ILAST  IPRF
  2  64  1  2   0.25  0.  3  1  32  0 
CC
CC WELL NAME
*----- WELNAM 
PRODUCER 
CC
CC ICHECK, MAX. AND MIN. ALLOWABLE BOTTOMHOLE PRESSURE AND RATE
*-----ICHECK PWFMIN  PWFMAX  QTMIN  QTMAX
  2  0.0  100000.  0.0  100000. 
CC
CC ID,INJ. RATE AND INJ. COMP. FOR RATE CONS. WELLS FOR EACH PHASE (L=1,3)
*-----ID  QI(M,L)  C(M,KC,L)
  1  100.  1.0  0.0  0.000  0.4  0.003  0.0  0. 
  1  0.  0.  0.  0.  0.  0.  0.  0. 
  1  0.  0.  0.  0.  0.  0.  0.  0. 
CC
CC ID, BOTTOM HOLE PRESSURE FOR PRESSURE CONSTRAINT WELL (IFLAG=2 or 3)
*-----ID PWF
  2  100.
CC
CC CUM. INJ. TIME, AND INTERVALS (PV or DAY) FOR WRITING TO OUTPUT FILES
*-----TINJ CUMPRI cumh1 WRHPV WRPRF RSTC
  1.00  0.05  0.05  0.05  0.05  0.2
CC
CC FOR IMES=2, THE INIT. TIME STEP, CONC. TOLERANCE, MAX., MIN. COURANT NUMBERS
*-----DT DCLIM CNMAX CNMIN
  1  0.1  0.5  0.001
CC
*--- ibmod
  0
CC
CC IRO, ITIME, NEW FLAGS FOR ALL THE WELLS
*----- IRO ITSTEP IFLAG
  2  1  1  2
CC
CC NUMBER OF WELLS CHANGES IN LOCATION OR SKIN OR PWF
*-----NWEL1
  0
CC
CC NUMBER OF WELLS WITH RATE CHANGES, ID
*-----NWEL1 ID
  1  1
CC
CC ID, INJ. RATE AND INJ. COMP. FOR RATE CONS. WELLS FOR EACH PHASE (L=1,3)
*-----ID QI(M,L) C(M,KC,L)
  1  100.  0.94  0.  0.03  0.06  0.2  0.001  0.03  0.
  1  0.   0.  0.  0.  0.  0.  0.  0.  0.
  1  0.   0.  0.  0.  0.  0.  0.  0.  0.
CC
CC CUM. INJ. TIME, AND INTERVALS (PV) FOR WRITING TO OUTPUT FILES
*-----TINJ CUMPRI cumh WRHPV WRPRF RSTC
  1.10  0.05  0.05  0.05  0.05  0.2
CC
CC FOR IMES=2, THE INIT. TIME STEP, CONC. TOLERANCE, MAX., MIN. TIME STEPS
*-----DT DCLIM CNMAX CNMIN
  0.0001  0.01  0.01  0.001
CC
*--- ibmod
  0
CC
CC IRO, ITIME, NEW FLAGS FOR ALL THE WELLS
*----- IRO ITSTEP IFLAG
  2  1  1  2
CC
CC NUMBER OF WELLS CHANGES IN LOCATION OR SKIN OR PWF
*-----NWEL1
  0
CC
CC NUMBER OF WELLS WITH RATE CHANGES, ID
*-----NWEL1 ID
  1  1
CC
CC ID, INJ. RATE AND INJ. COMP. FOR RATE CONS. WELLS FOR EACH PHASE (L=1,3)
*-----ID QI(M,L) C(M,KC,L)
  1  100.  1.  0.  0.0  0.06  0.2  0.001  0.0  0.
  1  0.   0.  0.  0.  0.  0.  0.  0.  0.
  1  0.   0.  0.  0.  0.  0.  0.  0.  0.
CC
CC CUM. INJ. TIME, AND INTERVALS (PV) FOR WRITING TO OUTPUT FILES
*-----TINJ CUMPRI cumh WRHPV WRPRF RSTC
  1.20  0.05  0.05  0.05  0.05  0.2
CC
CC FOR IMES=2, THE INIT. TIME STEP, CONC. TOLERANCE, MAX., MIN. TIME STEPS
*-----DT DCLIM CNMAX CNMIN
  0.01  0.01  0.1  0.001
CC
CC
*--- ibmod
  0
CC
CC IRO, ITIME, NEW FLAGS FOR ALL THE WELLS
*----- IRO ITSTEP IFLAG
  2  1  1  2
CC
CC NUMBER OF WELLS CHANGES IN LOCATION OR SKIN OR PWF
*----- NWEL1
  0
CC
CC NUMBER OF WELLS WITH RATE CHANGES, ID
*----- NWEL1 ID
  1  1
CC
CC ID, INJ. RATE AND INJ. COMP. FOR RATE CONS. WELLS FOR EACH PHASE (L=1,3)
*----- ID QI(M,L) C(M,KC,L)
  1   100.  1.  0.  0.  0.  0.4  0.003  0.0  0.
  1   0.    0.  0.  0.  0.  0.  0.  0.  0.
  1   0.    0.  0.  0.  0.  0.  0.  0.  0.
CC
CC CUM. INJ. TIME, AND INTERVALS (PV) FOR WRITING TO OUTPUT FILES
*----- TINJ CUMPR1 cumh WRHPV WRPRF RSTC
  10.05  0.05  0.05  0.05  0.05  0.2
CC
CC FOR IMES=2 , THE INIT. TIME STEP, CONC. TOLERANCE, MAX., MIN. TIME STEPS
*----- DT DCLIM CNMAX CNMIN
  0.03  0.03  0.1  0.001

153
Appendix D: Convection Dispersion Curve Fitting

The following code was used in Microsoft Excel Visual Basic Applications (VBA) to automate the curve fitting process of local block tracer concentrations with time. Solver was used with two tuning parameters, Peclet number, $N_p$, and a shift parameter, $\Delta t_{\text{shift}}$, to synchronize dimensionless time in terms of pore volumes injected (PVI). This shift parameter was introduced to horizontally align the simulation output to the model estimation, allowing the best-fit of the curve in terms of $N_p$. This shift is required as the reservoir used is two-dimensional and is being approximated by the one-dimensional CD equation. To remove the error associated with injection time due to this additional dimension the shift parameter alleviates the strain on the equation by allowing the fit curves and output concentration histories to be aligned. This focuses the curve-fitting process on the Peclet number, which is the important factor, as the shift is merely an adjustment used to best calculate the level of simulated dispersion.

Sub Fill()
    Dim i As Integer
    For i = 1 To 64
        SolverReset
        SolverOk SetCell:=Range("ALH5:ALH36").Cells(i, 1), MaxMinVal:=2, ValueOf:="0",
        ByChange:=Range("ALF5:ALG36").Rows(i)
        SolverAdd CellRef:=Range("ALG5:ALG36").Cells(i, 1), Relation:=3,
        FormulaText:="0.001"
        SolverOptions Assumenonneg:=False
        SolverSolve True
    Next i
End Sub