Well Placement Optimization for Maximum Energy Recovery from Hot Saline Aquifers

Esmail Ansari, Richard Hughes, Christopher D. White Craft and Hawkins Department of Petroleum Engineering Louisiana State University Baton Rouge, LA 70803, USA eansar2@lsu.edu

Keywords: geothermal reservoir, hot saline aquifer, well placement, natural convection, energy recovery, Louisiana, US Gulf Coast

ABSTRACT

Hot saline aquifers are a large potential geothermal resource for the US Gulf coast. These geopressured reservoirs could produce geothermal energy because of their high pressures and permeabilities, in spite of their moderate temperatures of circa 140°C. Although these resources have been researched extensively, previous investigations have reached mixed conclusions regarding the technical and economic feasibility of these reservoirs. Gulf Coast geothermal reservoir development is further complicated by the requirement to dispose of the high-salinity produced brine with minimal environmental and geomechanical risk. Injection of cooled brine reduces reservoir temperature and may affect the well productivity and economic performance. Decisions on the location of the injection and production wells are important for estimating energy recovery.

This article provides estimates of energy generation using reasonable approximations for the study site, the Camerina A zone of the Gueydan field, Vermilion Parish, Louisiana. Well locations in the field are optimized with net enthalpy recovery for a 30 year project life as the objective function. A subset of existing wells originally drilled for oil exploration purposes are used for modeling geothermal exploitation. The results confirm that injection into cooler areas of the reservoir and producing from hotter regions is the best heat harvesting strategy. The results include simple performance models available for binary power plants. Louisiana geothermal resources, previously viewed as marginal, appear to be feasible targets for geothermal energy production.

1. INTRODUCTION

The search for clean alternative energy resources to replace fossil fuels is important for securing the world's energy future and reducing global warming. Geothermal energy is an environmentally benign alternative, although only a small fraction can be economically produced with current technology. Thirty percent of the world's geothermal energy is produced in the USA, mostly in California and Nevada (Geothermal Energy Association, 2012). The US Gulf Coast has geothermal energy potential in hot geopressured aquifers that have been extensively penetrated and mapped in the process of oil and gas exploration.

Louisiana's geopressured sedimentary aquifers have been examined previously (Bassiouni, 1980; Bebout et al., 1981; McMullan and Bassiouni, 1984). However, these resources have not been developed, and uncertainty associated with their economics persists. Quitzau and Bassiouni (1981) used Monte Carlo sampling to assess the effects of uncertainty on the controlling parameters to evaluate commercial production of dissolved gas from Louisiana's geothermal resources. They concluded that development of these reservoirs was not economically viable. However, they indicated that conversion of an unsuccessful oil or gas well into a geopressured brine well could be economically feasible if any environmental and legal concerns could be overcome.

Griggs (2004) examined coproduction of geothermal energy and its dissolved natural gas. He used experimental design and response surface to evaluate coproduction from Louisiana's geothermal reservoirs and concluded that a minimum bulk volume of 1.05 cubic kilometers is required for a single well to be a candidate for geothermal and methane coproduction.

Gray and Nunn (2010) studied the geothermal energy potential associated with salt domes near the Camerina A zone of the Gueydan field in Louisiana. They found that heat flow through the salt dome had limited impact on the geothermal potential of the reservoir because of the moderate burial depth.

Plaksina et al. (2011) studied the effects of coupled free convection and CO_2 injection on heat extraction from an idealized sedimentary geothermal reservoir. Their work indicated that more than 25 percent of the sensible energy could be extracted in a 30 year project life. They also compared the effect of wellbore chilling with geofluid production for heat extraction and showed that production is more effective. They did not assess the maximum net energy that could be produced from an actual geopressured geothermal reservoir.

Over the last decade, injection of cooled brine back into geothermal reservoirs has been increasing (Goyal, 1999; Axelsson and Dong, 1998). Brine injection changes the chemistry of the fluid (possibly causing unfavorable rock-fluid interactions), lowers reservoir

temperature, and may cause subsidence because of thermal expansivity (Stefansson, 1986). The location and rate of injection must be designed to minimize these unfavorable effects, especially to delay thermal breakthrough at the producers.

Based on the conclusions of Quitzau and Bassiouni (1981) and Griggs (2004), abandoned wells at the top of the Camerina A sand in the Gueydan field are considered as candidates for recompletion as part of a geothermal development program. This study optimizes producer and injector locations to maximize the enthalpy recovery from the reservoir. The number of well combinations for this problem is large and requires many reservoir simulation runs. We select four production and four injection wells out of eleven abandoned wells, which requires 11,550 runs. Such problems require efficient and robust optimization to obtain the solution with a feasible number of simulations.

Algorithms for well placement optimization problems can be categorized into three groups: gradient-based techniques (Sarma and Chen, 2008; Bangerth et al., 2006), proxy methods (Onwunalu et al., 2008; Wang et al., 2012) and global search stochastic algorithms (Tupac et al., 2007; Farshi, 2008). Gradient-based optimization methods improve the objective function by stepping the vector of parameters in a direction based on matrices of partial derivatives of the objective function with respect to the parameters. Gradient methods commonly converge to false (local) optima. In the context of geothermal engineering, Akın et al. (2010) used proxy methods to optimize injection well locations in the Kizildere geothermal field. Proxy models are computationally fast but approximate the objective function using a limited suite of preselected reservoir models. These response models may be inaccurate, particularly for nonlinear and undersampled cases. Onwunalu and Durlofsky (2010) showed the superior performance of particle swarm optimization (PSO; a stochastic global search method) compared with genetic algorithms. Afshari et al. (2011) showed that improved harmony search, another global search method, performs well for well location optimization. However, stochastic algorithms are heuristic and require parameter tuning; it is difficult to reach general conclusions about the best method for any particular case. This study used a particle swarm optimization algorithm (Computer Modeling Group Ltd, 2011a) for optimization.

This paper proceeds as follows: first, the PSO algorithm is summarized. The geologic and engineering context for the Camerina A reservoir is described before clarifying the objective of the withdrawal design and enumerating the approximations used in this work. Simulations show that free convection is likely to be significant for the subject reservoir, and free convection is combined with forced convection in simulations of the development of the reservoir. General implications are discussed before offering conclusions.

2. PARTICLE SWARM OPTIMIZATION (PSO)

The PSO algorithm is a stochastic population-based optimization method in which each *particle* is a point (i.e., a candidate solution) in the search space (Eberhart and Kennedy, 1995). The collection of these particles is called a *swarm*. Particle movement is governed by simple rules, which attempt to avoid local extrema and continue to search the parameter space for the optimal solution.

For an objective function with *n* parameters to be optimized, a particle is represented by $\mathbf{x}_i(k) = (\mathbf{x}_{(i,1)}(k), \mathbf{x}_{(i,2)}(k), \dots, \mathbf{x}_{(i,n)}(k))$ in which i is the number of the particle and k is the iteration. The previous best solution for the ith particle through iteration k is denoted by $\mathbf{x}_i^{\text{pbest}}(k)$ and the position of the best particle in the neighborhood of particle i up to iteration k is $\mathbf{x}_i^{\text{nbest}}(k)$. A simplified particle swarm case uses one group of particles; thus the global best particle position is the same as the neighborhood best position for all the particles. The *i*th particle is moved (Eq. 1) and its new position is evaluated at iteration k in the parameter space using

$$\mathbf{x}_{i}(k+1) = \mathbf{x}_{i}(k) + \mathbf{v}_{i}(k+1)$$
 (1)

in which $\mathbf{v}_i(k+1) = (\mathbf{v}_{(i,1)}(k+1), \mathbf{v}_{(i,2)}(k+1), \dots, \mathbf{v}_{(i,n)}(k+1))$ represents the parameter-space velocity of the ith particle at the (k+1)th iteration. The velocity vector is calculated using Eq. 2:

$$\mathbf{v}_{i}(k+1) = \omega \cdot \mathbf{v}_{i}(k) + c_{1} \left(\mathbf{D}_{1}(k) \left(\mathbf{x}_{i}^{\text{pbest}}(k) - \mathbf{x}_{i}(k)\right)\right) + c_{2} \left(\mathbf{D}_{2}(k) \left(\mathbf{x}_{i}^{\text{nbest}}(k) - \mathbf{x}_{i}(k)\right)\right)$$
(2)

in which $\mathbf{D}_i(\mathbf{k})$ are matrices whose diagonal elements are uniformly distributed random variables in the range [0,1], and ω , c_1 and c_2 are weights. The values of ω , c_1 and c_2 are chosen heuristically and depend on the type of the problem. Procedures to optimize these values have been developed for well placement optimization (Onwunalu and Durlofsky, 2010). There are three terms in Eq. 2, known as inertia (the term with ω), cognitive (the term with c_1) and social (the term with c_2) respectively. The inertia term assures that the particle velocity is somewhat persistent from one iteration to the next. The cognitive term moves the particle along its own previous best position whereas the social term moves the particle towards the best particle in its neighborhood. These three terms move the particle toward extrema. The inertia term provides a broad exploration of the search space and the cognitive and social terms move the particle towards the best solutions found (up to the current iteration).



Figure 1: PSO algorithm in two-dimensional space. The $(k+1)^{th}$ movement of the ith particle is the vector sum of inertia $v_i(k)$, cognitive $v_i^{c}(k)$ and social $v_i^{s}(k)$ components proportional to their coefficients (After Onwunalu and Durlofsky, 2010).

The vector sum of the inertia, cognitive and social terms determines the next movement of the particle (two dimensional example, Fig. 1). In this figure, $\mathbf{v}_i(k)$ is the particle's previous velocity, $\mathbf{v}_i^c(k)$ shows the cognitive velocity from the current position $\mathbf{x}_i^{\text{pbest}}(k)$, and $\mathbf{v}_i^s(k)$ is the social velocity from the current position to the current neighborhood best position $\mathbf{x}_i^{\text{nbest}}(k)$. The next movement of the ith particle is then calculated by adding the weighted $\mathbf{v}_i(k)$, $\mathbf{v}_i^c(k)$ and $\mathbf{v}_i^s(k)$ vectors.

3. THE CAMERINA A MODEL

The Camerina A geopressured reservoir in the Gueydan field lies between 4200 and 4600 m subsea depth with a dip range from 1.2 to 28° on the north and south edges of the four way closure (Fig. 2). A shale sequence ranging from 365 to 426 m thick overlies the Camerina A sand and a 150 m shale sequence is below it. The Camerina A structure has a four way closure, with one side bounded by a salt dome. The model does not consider thermal conduction through the salt dome because it does not affect heat production from the Camerina A (Gray and Nunn, 2010). The model uses a corner point grid with dimensions of the *x-y-z* grid count of $25 \times 32 \times 3$. Each grid block is 200 m on the sides and the thickness of the reservoir is divided into three layers that equally divide the areally varying thickness (top layer thickness, Fig. 3).



Figure 2: Structural map of the Camerina A The elongate dome is ca. 300 m above the surrounding region, which may provide a driving force for convection. Dips range up to 28 degrees. Void blocks are not colored in all grid displays (after Gray and Nunn (2010)).



Figure 3: Isopach map of the Camerina A. The thickest reservoir interval approximately conforms to the structure top (compare Fig. 2). This is a region with relatively high productivity, and storativity (after Gray and Nunn (2010))

Homogeneous horizontal and vertical permeabilities are 300 md and 30 md respectively. Thermal conductivity of the cap and base rock, the reservoir rock and water were set to 1.496×10^5 , 6.6×10^5 and 5.35×10^4 J m⁻¹ day⁻¹ °C⁻¹ respectively. Thermal capacity of the cap and base rock and the reservoir rock were set to 2.347×10^6 and 1.97×10^6 J m⁻³°C⁻¹, respectively and properties of the water were calculated from steam tables (Computer Modeling Group Ltd, 2011b).

The initial pressure of the reservoir was assumed to be a uniform 80 MPa and the only variation in the initial pressure of the model is caused by the buoyancy and viscosity differences in the fluid during model initialization. The temperature of the zone varies between 128 and 150 $^{\circ}$ C from the top to the bottom of the sand (Fig. 4). Vertical wells were completed in all three layers of the model and were controlled using a constant flow rate constraint.

Net-to-gross ratios were only known at the wells and were kriged to estimate values for the other cells. The net-to-gross ratio relaxes to its average value away from available data. Rocks and fluids have different thermal characteristics, thus using net-to-gross ratio values helps to capture the effects of these differences.



Figure 4: Initial reservoir temperature of the Camerina A. There is significant temperature variation caused by elevation, geothermal gradient, and free convection (after Gray and Nunn (2010)).

The model was initialized at constant potential, and the natural convection pattern was obtained by simulating 1000 years with no injection or production. Production starts after this initial state of the model is reached and continues for 30 years.

4. DESIGN AND ASSUMPTIONS

We consider a mass withdrawal design in which all brine that is produced from the reservoir is injected back into the reservoir. The total heat recovery during 30 years of geofluid production from the reservoir is then calculated. Binary power plants associated with low enthalpy geothermal reservoirs can have voidage-replacement ratios approaching one (DiPippo, 2012). Further, binary power plants require ca. $2500-4000 \text{ m}^3 \text{ day}^{-1}$ of low enthalpy geothermal fluid to be economically viable. For the case studied here, eight vertical wells (four production and four injection) are used to deliver $8000 \text{ m}^3 \text{ day}^{-1}$ (approximately two times the nominally required amount). Other assumptions are:

1- No history matching was done and the geologic model was fixed.

2- Eleven abandoned wells at the top of Camerina A zone were chosen as candidate wells for the geothermal development. Out of these eleven, three wells were not used, four wells were chosen for production and four wells for injection. It is assumed that these wells can be restored for production and injection purposes (Quitzau and Bassiouni, 1981; Griggs, 2004).

3- No chemical reaction from cool water injection is considered. Thus the permeability and porosity do not change and injection into the reservoir is not impaired. Power for the injection pump is not included in net energy calculations.

4- The flow rate constraint on each well is $2000 \text{ m}^3 \text{ day}^{-1}$. These values were chosen to be lower than well test results from similar zones in Louisiana (John et al., 1998).

A thermal reservoir simulator (Computer Modeling Group Ltd, 2011b) was used for computing the heat recovery from the reservoir model. The model requires 11,550 numerical reservoir simulations for all well combinations. A particle swarm algorithm (Computer Modeling Group Ltd, 2011a) was used for determining the best well locations for maximum heat recovery within 500 runs. Values for ω , c_1 and c_2 were set to 0.6, 1.6 and 1.6 respectively and 10 particles were considered for the population size.

5. RESULTS

The thermal state of the model after the initial 1000 years with no injection or production is nearly identical to that provided by the mapping of temperatures from well data (compare Figs. 4 and 5). There are three natural convection cells in the model (Fig. 5), with the highest flux arrow correspond to velocities of ca. $3.3 \text{ m'day}^{-1} \sim 3.8 \times 10^{-5} \text{ m s}^{-1}$. A mean interstitial fluid velocity of $3 \times 10^{-5} \text{ m s}^{-1}$ for most aquifers is a high value (Phillips, 2009). The natural convection is created by buoyancy and elevation differences in the model and is small near the boundaries. This initial state is used for the forced convection (heat extraction) studies that follow. Details of the wells are presented in Table 1.



Figure 5: Predicted equilibrium state for the Camerina A geothermal reservoir. Three natural convection cell in the reservoir can be detected after the equilibrium state is reached. The longest flux arrows correspond to velocities of ca. 3.3 m d⁻¹.

The particle swarm optimization used 500 model runs and 10 particles for the population size, and assumed that the wells could be selected with replacement. However, the optimization sometimes naively selected wells more than once. After eliminating the infeasible cases, the optimal feasible is predicted to produce 2.72×10^{16} J. The optimization task took ca. 825 minutes to complete.

The temperature response in the production wells (Fig. 6) depends on the well locations in the field (Fig. 7). The average temperature for the mixed fluid varies between 140-142 °C. The John B Baker et al #1 well shows a steady temperature and produces the highest enthalpy. The temperature of the Gordon D Riley et al. #1 has a concave down decline due to being located in a low temperature section of the reservoir (as compared to other production wells) and due to its proximity to injection wells. The temperature of the Maggie B Lusk et al #1 well increases as geofluid from the hotter sections of the reservoir flows toward it. The temperature drop in the Alliance Trust Co. #19 well is less than the Gordon D Riley et al. #1 well because it is located farther from the injection wells.

Table 1: Detail of the wells			
Well	Mid-perf depth (m)	Perforation length (m)	Status
Gordon D Riley et al #1	4319	78	Producer
Maggie B Lusk et al #1	4374.4	24.7	Producer
John B Baker et al #1	4392.45	16.9	Producer
Alliance Trust Co. #19	4431.6	32.2	Producer
Rubie Hair LeBlanc et al #2	4324.05	67.3	Injector
Ruby Hair LeBlanc #1	4323.65	84.5	Injector
H.M. Hair Jr. #1	4462.7	9.8	Injector
SW LA Land Co. Inc. et al #1	4339.6	75.1	Injector
U Cam RB Lejune	4348.4	55.8	Not used
U Cam H M Hair Est	4301.1	42.22	Not used
SW LA Land Co Inc	4356.1	45.5	Not used

Downhole temperature of the production wells



Figure 6: Downhole temperature profile of the selected production wells. The well John B Baker et al #1 shows a steady temperature and produces the highest enthalpy.

The optimization places production wells in the hotter sections of the reservoir while the injection wells are located in the cooler areas of the reservoir (Fig. 7). Thermal breakthrough in the Gordon D Riley et al #1 well causes a decline in its temperature. For developing Gulf Coast geothermal projects, design of brine injection should emphasize thermal sweep of the reservoir because reservoir pressure is high enough to ensure adequate productivity. For the Camerina A, injection of cooled brine into the reservoir periphery (which has lower temperatures) and producing from the hot areas gives the highest thermal sweep.



Figure 7: Reservoir temperature after 30 years of the geofluid injection and production. Thermal breakthrough in the Gordon D Riley et al #1 well causes a rapid decline in its temperature.

After 30 years of production, reservoir pressure remains high (Fig. 8). The production of geofluid reduces the pressure around the production wells; injecting all of the cooled geofluid maintains the pressure around the injection wells. Near the boundaries, the pressures around the production wells decline more and pressures around the injection wells increase more than those away from the boundaries. In particular, the H.M. Hair Jr. #1 well is located in a low net-to-gross section of the reservoir and its surrounding pressure increases rapidly due to lower reservoir quality. Although the injected brine maintains reservoir, the main reason for injection is disposal of the saline water. Production wells can likely sustain higher geofluid production rates because pressure declines are modest.

6. DISCUSSION

The maximum net energy that can be extracted from the Camerina A zone using the suggested design is 2.72×10^{16} J for 30 years. The wells have similar constant production rates and the average temperature of the mixed geofluid is calculated to increase from 141.8 to 142.1 °C after eleven years and then drop to 140.5 °C. The Camerina A is a low enthalpy geothermal reservoir (less than 150 °C), thus requiring a binary power plant. A Carnot cycle provides an upper bound on the efficiency of any power plant operating between a low temperature (here, the injection temperature T_{inj}) and a high temperature (here, production temperature T_{prod}). The Carnot relation is:

$$\eta = 1 - T_{ini} / T_{prod} = 1 - (70 + 273.15) / (140 + 273.15) = 17\%$$
(3)

The Carnot estimate for the assumed conditions is 4.88 MW. Binary cycles are less efficient than the Carnot. A more realistic cycle for calculating thermal efficiency of a binary plant is a triangular cycle. In this cycle, the brine transfers heat to a working fluid in an isobaric state (ca. 80 MPa) instead of an isothermal state that Carnot cycle assumes. The geofluid cools as it passes through heat exchanger in an isothermities expansion. The brine is finally injected into the reservoir in an isothermal process (ca. 70°C). The triangle rule (Eq. 4) yields a thermal efficiency of 9.26 percent:

$$\eta = (T_{\text{prod}} - T_{\text{ini}})/(T_{\text{prod}} + T_{\text{ini}}) = 9.26\%$$
(4)

The small temperature differences between the production and injection wells result in low thermal efficiency. The triangle cycle suggests maximum average power (using the average produced fluid temperature) of 2.67 MW for the Camerina A model scenario. Considering that the average rate of electricity consumption per person is about 0.5 kW, estimated the 2.67 MW of electricity would be sufficient to provide electricity for ca. 5000 persons for a period of 30 years.



Figure 8: Reservoir pressure distribution after 30 years of geofluid injection and production. The production of geofluid for 30 years reduces the pressure of the reservoir around production wells and injecting constant flow rate cooler brine increases the pressure around the injection wells.

Chandrasekharam and Bundschuh (2008) give an approximate formula for calculating the power production from geothermal systems: a flow rate of 25 to 27 l s⁻¹ with a temperature between 140 to 147 °C can produce 1 MW electricity. Using this approximation, the Camerina A scenario producing 92 l s⁻¹ is capable of generating 3 to 4 MW of electricity.

Finally, because the pressure of the Camerina A zone remains high during its exploitation (Fig. 8), downhole pumps are not needed to assist production.

7. CONCLUSIONS

The primary reason for brine injection into geopressured aquifers is to dispose highly saline water and to mitigate geomechanical risk. For developing U.S. Gulf Coast geothermal projects, injection of brine should be designed to maximize thermal sweep of the reservoir. Because the pressure of these reservoirs is already high, the thermal sweep is more important than pressure maintenance. This study shows that injection of cool brine into the Camerina A zone along the peripheral sections which have lower temperature and producing from the hot sections of the reservoir results in the highest thermal sweep. With the design proposed in this work, a system like the Camerina A reservoir could produce at least 2.5 MW power for over thirty years.

8. ACKNOWLEDGMENTS

The authors gratefully acknowledge financial support for this work from the US Department of Energy under grant DE-EE0005125. We thank Computer Modeling Group for providing reservoir simulation software. We also thank the members of the LSU Geothermal team for their comments, suggestions and ideas supporting our efforts.

REFERENCES

- Afshari, S., Aminshahidy, B. and Pishvaie, M. R.: "Application of an Improved Harmony Search Algorithm in Well Placement Optimization Using Streamline Simulation", *Journal of Petroleum Science and Engineering*, **78** (3), (2011), 664-678.
- Akin, S., Kok, M. V. and Uraz, I.: "Optimization of Well Placement Geothermal Reservoirs Using Artificial Intelligence", Computers & Geosciences, 36 (6), (2010), 776-785.
- Axelsson, G. and Dong, Z.: "The Tanggu Geothermal Reservoir (Tianjin, China)". Geothermics, 27 (3), (1998), 271-294.
- Bangerth, W., Klie, H., Wheeler, M., Stoffa, P. and Sen, M.: "On Optimization Algorithms for the Reservoir Oil Well Placement Problem", *Computational Geosciences*, **10** (3), (2006), 303-319.
- Bassiouni, Z.: Evaluation of Potential Geopressure Geothermal Test Sites in Southern Louisiana, Technical Report, Louisiana State University, Baton Rouge (USA), Dept. of Petroleum Engineering, (1980).
- Bebout, D., Gutierrez and D., Bachman, A: *Geopressured Geothermal Resource in Texas and Louisiana: Geological Constraints*. Technical Report, Louisiana Geological Survey, Baton Rouge, (1981).

Chandrasekharam, D. and Bundschuh, J.: Low-enthalpy Geothermal Resources for Power Generation, CRC Press, (2008).

Computer Modeling Group Ltd: CMOST Manual, Calgary, AB, Canada, (2011a).

Computer Modeling Group Ltd: STARS Manual: Advanced Process and Thermal Reservoir Simulator. Calgary, AB, Canada, (2011b).

- DiPippo, R.: Geothermal Power Plants: Principles, Applications, Case Studies and Environmental Impact, Butterworth-Heinemann, (2012).
- Eberhart, R. and Kennedy, J.: "A New Optimizer Using Particle Swarm Theory, Micro Machine and Human Science", MHS'95., *Proceedings*, Sixth International Symposium on IEEE, (1995), 39-43.
- Farshi, M.: Improving Genetic Algorithms for Optimum Well Placement, Ph.D. Thesis, Stanford University, (2008).
- Geothermal Energy Association: Geothermal: International Market Overview Report (2012).
- Goyal, K.: "Injection Related Cooling in the Unit 13 Area of the Southeast Geysers, California, USA", *Geothermics*, **28** (1), (1999), 3-19.
- Gray, T. and Nunn, J.: "Geothermal Resource Assessment of the Gueydan Salt Dome and the Adjacent Southeast Gueydan Field, Vermilion Parish, Louisiana", *Gulf Coast Association of Geological Societies Transactions*, **60**, (2010), 307-323.
- Griggs, J.: A Reevaluation of Geopressured-geothermal Aquifers as an Energy Resource. M.Sc. Thesis, Louisiana State University, (2004).
- John, C.J., Maciasz, G and Harder, B.J.: Gulf Coast Geopressured-Geothermal Program Summary Report Compilation, Work Performed Under U.S. Department of Energy, Contract No. DE-FG07-95ID13366, (1998).
- McMullan, J. H. and Bassiouni, Z.: "Prediction of Maximum Flow Rates from Geopressured Aquifers", Journal of petroleum technology, 36 (3), (1984), 503-509.
- Onwunalu, J., Litvak, M., Durlofsky, L. and Aziz, K.: "Application of Statistical Proxies to Speed up Field Development Optimization Procedures". *Abu Dhabi International Petroleum Exhibition and Conference*, (2008)
- Onwunalu, J. E. and Durlofsky, L. J.: "Application of a Particle Swarm Optimization Algorithm for Determining Optimum Well Location and Type". *Computational Geosciences*, **14** (1), (2010),183-198.
- Phillips, Owen M.: Geological Fluid Dynamics, Sub-surface Flow and Reactions, Cambridge University Press, (2009).
- Plaksina, T., White, C., Nunn, J. and Gray, T.: "Effects of Coupled Convection and CO₂ Injection in Stimulation of Geopressured Geothermal Reservoirs", *Proceedings*, 36th Workshop on Geothermal Reservoir Engineering, Stanford University, (2011), 146-154.
- Quitzau, R. and Bassiouni, Z.: "The Possible Impact of the Geopressure Resource on Conventional Oil and Gas Exploration". SPE Annual Technical Conference and Exhibition, (1981).
- Sarma, P. and Chen, W.: "Efficient Well Placement Optimization with Gradient-based Algorithms and Adjoint Models". *Intelligent Energy Conference and Exhibition*, (2008).
- Stefansson, V.: Geothermal Reservoir Managements, United Nations Project, PHI-080-014, Manila. (1986), 1-45.
- Tupac, Y., Almeida, L. and Vellasco, M.: "Evolutionary Optimization of Oil Field Development". *Digital Energy Conference and Exhibition*, (2007).
- Wang, H., Echeverr a Ciaurri, D., Durlofsky, L. and Cominelli, A.: "Optimal Well Placement Under Uncertainty Using a Retrospective Optimization Framework", SPE Journal, 17 (1), (2012), 112-121.