

Modeling grids with 4 subgrids (St Louis A, B, C and D)



The grid was built with equal X and Y increment to 500 ft and a constant layer thickness = 2 feet parallel to bottom surface within the St Louis A, B, C and D subgrids in Z axis.

Geometry data for modeling facies

Faices Name		Averaged Minimum	Averaged Maxmum		Source	
Ooid Shoal	Thickness	3 ft	11 ft	Angiant		
	Length	0.75 miles		Ancient		
	Dip length	1.5 miles	2.7 miles	Modern	Kelly Bergman, et, 1998	
	Strike length	3.9 miles	6.4 miles			
Tidal Flat	Thickness	2 ft	15 ft	Ancient		
	Length	0.25	12.5 miles			
	Thickness	6.5 ft	28 ft	Modern		
	Dip length	0	25 miles			
	Strike length	8.75 miles	45 miles			
Eolianite	Thickness	4 ft	22 ft	Ancient	F.E.Abegg, et, 2001	
	Dip length	0.25 miles	18 miles			
	Thickness	10 ft	50 ft	Modern		
	Dip length	0	30 miles			
	Strike length	10 miles	70 miles			

Ooid shoal, tidal flat and eolianite dune generally all have strike-elongated geometry Above table summarizes the general 3D geometry data of these facies from Bergman, 1998 and Abegg, 2001. Final geometry data was selected after various trials to fit the Mississippian St Louis carbonate system.

Original well data (lithofacies, porosity, perm and Sw) have been upscaled to the grid size after importing to geostatistical simulation project. Facies logs have been treated as blocked within a facies interval. Average values have been blocked into the grid cells for continuous logs.

Argillaceous limestone (deep marine) and skeletal wackestone (open marine) were combined into marine facies and treated as the background facies (code=0) in modeling. Peloidal grainstone limestone was defined as tidal flat facies (code=1), and cross-bedded quartz-rich carbonate grainstone as eolianite facies (code=4). Ooid skeletal grainstone (code=2) and cemented ooid skeletal grainstone (code=3) were combined into oolitic shoal complex facies. Then, permeability barriers in the complex were modeled by merging the separately modeled cemented oolitic facies into the complex.

Comparison of the effect of different geometry and simulation proportion for oolitic shoal complex

Smaller geometry size with less proportion simulated

Raw log data

Blocked well data

Larger geometry size with more proportion simulated

Both show the same layer (Z=165) in the simulation grid









Simulation results for oolitic shoal complex



Facies proportion trend

Oolitic shoal complex proportion map



Tidal flat proportion map



Stochastic simulation result for facies









Eolianite proportion map







The histogram of porosity (oolitic grainstone) before the transforms



The histogram of porosity (all facies) afte the transform (truncation, scale-shift, and normal score).





histogram of permeability (all facies) after the transforms (truncation. scale-shif power and normal socre).

14 0.9 -0.6 -

C zone).

Stochastic simulation result for porosity









Stochastic simulation result for permeability



Stochastic simulation result for water saturation





Variogram Modeling



Porosity and permeability variogram models were built for all the facies modeled within 4 different subgrids. This variogram shows the modeling for oolitic grainstone facies in subgrid 3 (St Louis



Summary:

This poster illustrates the construction of an improved 3D stochastic model and simulation on St. Louis carbonate systems.

I. Six lithofacies were recognized and classified through the description of 10 cored wells of St. Louis oolite shoal reservoirs in Southwestern Kansas.

2. The reservoir lithofacies, ooid skeletal grainstone, has distinctive petrophysical properties.

Neural Network models were developed using digital logs (GR, Rt, PE and Porosity) from cored wells. Llithofacies were predicted in cored and non-cored wells with a high degree of accuracy.

4. Lithofacies predicted from Neural Network model can be interpolated between wells to better understand depositional patterns and external geometry of St Louis Limestone.

5. Stratigraphic surfaces were used to build a 3D stratigraphic framework.

6. Object-based stochastic modeling was performed to build lithofacies models in three St. Louis oolite reservoirs to better understand the 3D external geometries of St. Louis oolite shoals.

7. Internal geometries of St. Louis oolite shoal reservoirs were illustrated by building 3D porosity and permeability distribution models using stochastic simulation.

8. Multiple realizations can be built for all the stochastic simulation results

Further Work:

1. Add facies proportion trends and evaluate effect of azimuthal trend.

2. Rank the stochastic simulation models and select the reasonable models to upscale for streamline simulation test.

3. Compare the streamline simulation results and select the best model to export for flow simulation.

4. Perform reservoir simulation to verify the geostatistical models by production history match.

Reference:

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http://www.kgs.ku.edu/PRS/publication/2004/AAPG/3DReservoir