



COMPUTATIONAL TIME REDUCTION OF COMPOSITIONAL RESERVOIR SIMULATION MODEL WITH WAG INJECTION AND GAS RECYCLE SCHEME THROUGH NUMERICAL TUNING OF SUBMODELS

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ABSTRACT

This work shows a procedure to build fast and reliable numerical models with WAG-CO₂-rich injection scheme. This novel and practical approach to numerical tuning high-complexity reservoir models can save days or even months of work. Improving step 2 of the 12-step reservoir characterization and modeling methodology proposed by **Schiozer et al. (2015)** leads to an optimization of the numerical control of the model based on the critical compositional numerical parameters and performance diagnostics. We show the results of a probabilistic risk analysis application. For the complex case scenario presented, results show that applying the proposed technique can save roughly 80% of the total time spent to perform a risk study. Furthermore, we found that time saving tends to increase as the number of simulations increases. This work improvement comes from making a methodology that includes both compositional and black-oil numerical solver parameters in every step of the numerical tuning optimization, rendering a broader and more robust method.

KEYWORDS

reservoir simulation; numerical tuning; optimization; compositional simulation

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1. INTRODUCTION

This work focuses on improving step 2 of the 12-step methodology proposed by **Schiozer et al. (2015)** (Reservoir characterization and modeling). The main goal of this work is to optimize the numerical control of the model (tuning a compositional model) based on the critical compositional numerical parameters and performance diagnostics. The proposed methodology can be performed for black-oil and compositional reservoir numerical models with an appropriate parameterization. The present study offers an opportunity to minimize the total time spent running a compositional model. The dual-porosity and dual-permeability model used has a defined strategy of an offshore CO₂-rich water-alternated-gas (WAG) miscible reinjection, both with essential diagnostics of factors affecting computational time. This work allows the use of this model in compositional cases, which has already been done for black oil cases on any commercial reservoir simulator.

Li et al. (2014) performed a study concerning numerical tuning. According to the authors, the numerical tuning approach proved valid for improving the computational run time of simulation models, especially for large-scale complex ones. Following their study, one goal of numerical tuning is to find a set of numerical parameter values that make the simulation run faster with acceptable material balance error. In their work, the authors created a main global objective function, which is the weighted average of two functions (simulation run time and material balance error). They, then, optimized it using a single objective optimizer. To perform the numerical tuning, they used the optimizer Multiple Objective Particle Swarm (MO-PSO) on a submodel of a real field SAGD (Steam Assisted Gravity Drainage) model. Their MO-PSO aimed at reducing both the CPU run time and material balance error.

Card et al. (2014) performed an intricate work involving speedup and numerical tuning of a sizable full-field SAGD process simulation. The authors presented a workflow that enables running an extensive, multi-pad, full-field, multimillion cell SAGD simulation. Their workflow has three main steps: (1) generating geomodels that are easier for simulation, (2) using experimental design and 3D submodel choice for numerical tuning, and (3)

using 2D cross-section models to calibrate dynamic grid refinement for the entire 3D model. All steps aimed to enhance the numerical performance of multi-pad SAGD models. This same work includes a 24-SAGD-well-pair model with 2.52 million grid blocks, simulated for a ten-year forecast. The simulation time was reduced from 42 to 7 days on eight central processing units (CPU's) six times faster, using the proposed workflow. The authors claimed that, while this methodology is entirely generic and despite being developed for the SAGD process, it can be applied to any large simulation model of any process.

Avansi et al. (2019), from which our work was improved for the continuous scientific development on fast and reliable reservoir numerical models, also addressed the numerical tuning approach as crucial to reducing computational time and accelerating some probabilistic processes. Their approach included elements such as uncertainty analysis, production forecast, and decision analysis. In contrast to the work of **Li et al. (2014)**, **Avansi et al. (2019)** addressed general parameters from the Black-Oil model for the overall solver influence on run time. As a result, they developed a methodology consisting of numerical parameter choice, sensitivity analysis, optimization, diagnosis, tuning, and case study to provide reliable and practical initial values and configuration of the numerical section during simulations. All methodology steps require expert knowledge of the reservoir geology and reservoir properties that lead to a reduced simulation time, optimizing the number of solver failures, timestep cuts, and material balance error over the default configuration of the simulation model. The results of two case studies by **Avansi et al. (2019)** proved that we could: (1) accelerate the execution time up to 200% faster than the base case with default numerical section, (2) reduce failures and cuts, and (3) keep the material balance error within an acceptable value. Based on their conclusions, proportionally to the number of applications and runs, and varying with the heterogeneity of the simulation model, their work proved that it is possible to optimize the time spent in the reservoir team's frequent tasks and keep the material balance error and geological consistency by understanding the numerical behavior and optimizing the numerical section.

The work of **Avansi et al. (2019)** also enables smooth use of the controls and values of the numerical solver of the simulation model in reservoir simulation applications before running a massive number of simulations, which drastically reduced the run time.

Avansi et al. (2019) stated that efficient models run with the lowest effort proportional to the relevance of the study, availability of resources, and schedule.

To create complex and large simulation models, one must build these through a number of steps before starting any application in reservoir studies. One of these steps involves improving the numerical parameters of the numerical solver in the model to obtain a reliable production forecast (material balance) and save on execution time related to probabilistic reservoir management and development.

According to **Avansi et al. (2019)**, reservoir simulation teams often do not tune the best numerical section to run efficient simulation analysis tasks. An inappropriate numerical section can increase run time for a simulation task significantly. **Rios et al. (2020)** proposed a very efficient workflow, which evolved from **Avansi et al. (2019)**, by employing submodels to achieve numerical tuning for Black-Oil models with a reduced elapsed time. Most importantly, it allowed us to improve with the current numerical tuning step from **Rios et al. (2020)** for compositional models and make the procedure of **Avansi et al. (2019)** more general and valid for compositional cases.

Aside from the numerical parameter tuning, there are modeling details that substantially affect the simulation time, such as fracture implicitness, matrix-fracture fluid transfer functions, relative permeability curve shape, and grid orientation.

The innovative contribution of this work is to propose, for a complex compositional model of a realist offshore CO₂-rich WAG, a general methodology to optimize the simulation time of a WAG process numerically, achieving 80% of reduction in computational time by exploring the effects of tuning numerical solver parameters and submodels on the numerical performance of the simulation. This methodology is broader and more general than the previous ones because additional

parameters exclusive of the compositional numerical solver are included as much in the parameterization and sensitivity analysis as in the numerical optimization. There is no registered compositional case of numerical tuning as there is of Black-Oil.

1.1 The problem

After developing a reservoir simulation model, engineers use it in their daily tasks with one-run or multiple simulations to provide evaluations.

In this context, no particular care is given to the numerical section choice and key modeling options defining the numerical efficiency of the simulation.

Often, the default numerical section can be considered inefficient, while increasing the execution time also can twist the results with high material balance error.

There are cases where default numerical section and default modeling options can cause massive convergence failures and numerous timestep cuts, with interruptions to the simulation because of numerical failures or long execution time. When this happens, engineers often adjust the numerical parameters to deal with the issue in their daily tasks. If the problem involves a compositional model, many more numerical parameter sections are involved, rendering any manual or default numerical parameter adjustment very time-consuming. Occasionally, when the execution time issue cannot be solved, a more drastic upscaling is made to accelerate the runtime, instead of directly tuning the numerical solver setup of the model or testing parameters that are equally essential for speed efficiency and interaction with the simulation model. These time-consuming simulation models lead to many simplifications in the model, which can be avoidable. Also, these simplifications can be geologically inconsistent.

We believe engineers do not diagnose options critical for numerical performance for the reasons explained above, and less on compositional problems. They also lack this consideration before choosing a drastic upscale. Moreover, they do not calibrate the numerical section to accelerate the simulation model before using it on a task. The nature of the problem enhances the difficulties of a compositional problem, such as gas recycling, complex production systems, and multiphysics,

making it even more critical for the performance of numerical tuning. The focus of the current work is to adapt a useful and efficient method to improve the execution time of any kind of reservoir models and filtering material balance error acceptance parameters and numerical performance criteria.

1.2 Motivation

The excessive use of default or auto-tuned numerical parameters by engineers that work with reservoir simulation is widespread, even for the use of automatic tuning methods (adaptive timestep control, ADTSC on GEM) with the default options activated, due to the short time for checking the quality of the numerical model before starting reservoir studies. This procedure can harm the execution performance and obtain models with material balance error that are above the acceptance criteria. This is, therefore, our primary motivation: to provide support for all scientists working with practical procedures in reservoir simulation to tune a numerical model in a shorter period, using submodels for compositional problems that will yield better results than any option. In summary, the amount of time saved by tuning the model tends to increase as the number of applications increases.

There is no case registered in the literature for optimizing the numerical performance of compositional simulations, therefore, our work is innovative in this subject.

The studied case involves the use of compositional WAG simulation, with reinjection of total produced CO₂. This is one application necessary to study and simulate pre-salt scenarios.

1.3 Objectives

The main aim of this work is to propose a method to reduce the time for decision making using high time-consuming models under WAG injection, and to obtain reliable and consistent compositional numerical models to be used in daily routines of reservoir simulation studies, especially those with features from the pre-salt locations in Brazil.

Additional goals are:

- To develop a methodology compatible with different kinds of simulation, compositional, or

Black-Oil. Most methods developed previously are based on black oil, and there are several solver and parameter differences from this case.

- To improve numerical efficiency of compositional models in complex cases and achieve a comparable bulk gain in probabilistic risk analysis.

1.4 Assumptions

This work aims to develop a method to reduce the execution time of compositional models without losing accuracy. For this, we emphasize the assumptions considered in this work:

- Oil phase behavior is represented by compositional Peng-Robinson (Peng & Robinson 1978) EoS, 7 component PVT model;
- Reservoir simulation model is compared to default automatic parameter and settings;
- Fractures are represented by dual porosity, dual permeability model;
- Capillary pressure modeling is considered;
- Reservoir above bubble point pressure. Miscible gas injection is performed;
- History of production information from one wildcat well is available, i.e., focus on field development;
- Total produced gas reinjection;
- Modeling of the production system on the producer wells using multiphase flow tables;
- A single stochastic optimization is performed. We assumed a commercial software method, Yang et al. (2007), to tune the numerical settings of the model.

2. METHODOLOGY

The proposed methodology is improved from the work of Rios et al. (2020), with modifications highlighted in orange.

The steps on the workflow (Figure 1) from Rios et al. (2020) are adopted, with five main differences in steps 1, 2, 7, 8, and 9.

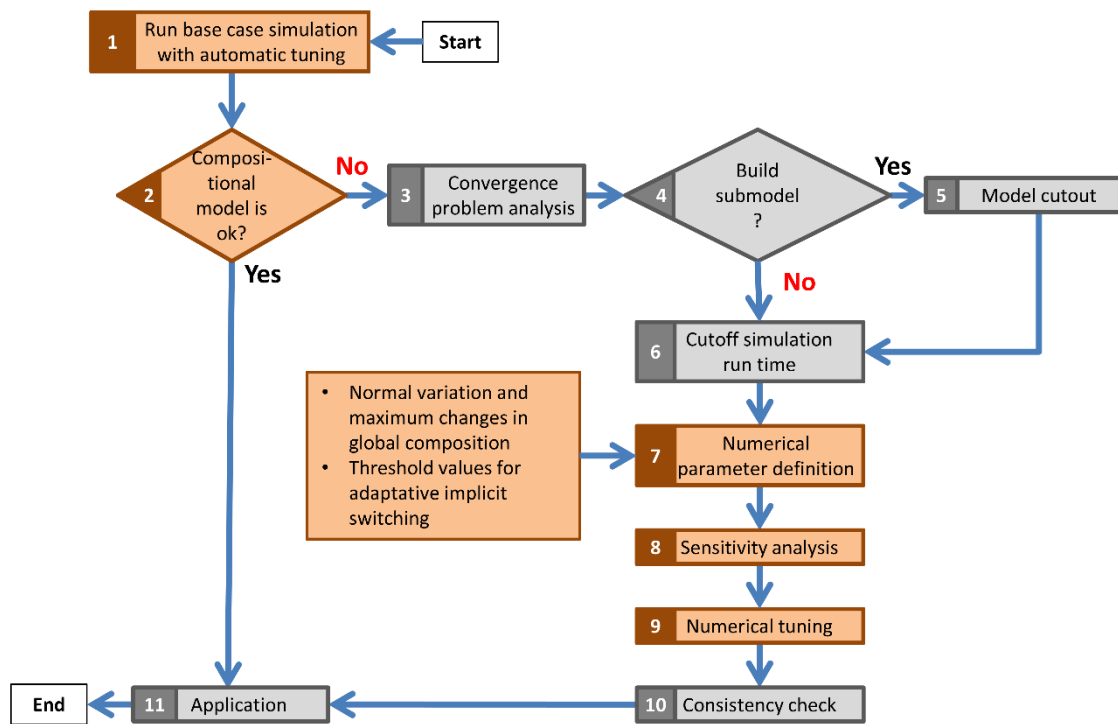


Figure 1. Workflow for optimization of numerical performance using submodels for a compositional reservoir simulation model. Modified from [Rios et al. \(2020\)](#).

Step 1 is vital for our proposed study because we consider as a base case run a model with all the default numerical control provided by the commercial simulator. Though we do not use any automatic calibration on our robust tuning (such as ADTSC), and we start from a simpler default base case (no automatic calibration) and perform better than any other, we need a control sample, so our best case is compared to a better base case than our simpler default. That base simulation runs either with or without the automatic default, which is quicker than the simpler default itself to test our capabilities. This automatic option in the compositional numerical simulator enables adaptive algorithms for timestep size selection and tunes numerical parameters to improve performance in a limited way. The way we defined our default case makes our comparison more

impressive in terms of challenges and computational time saved because its performance was far superior to the automatic default. One must note that automatic enhancement is mutually exclusive of our robust tuning, which is refined and more complex to implement. It is possible to use one or another, but they cannot overlap given the nature of automatic numerical calibration.

Step 2 is also crucial for our study. At this stage, we must define our acceptance criteria to validate the model within the required efficiency and based on the initial acceptance criteria. From the previous criteria, we improved the criterion for each of the numeric parameters defined for a compositional numerical simulation model. Table 1 includes the new criteria for this study.

Table 1. Acceptance set of criteria of compositional model performance based on the expertise of the reservoir geengineer and scientist.

Computational Statistics	Total _(o+w+g) MBE Error,	Number of Timestep Cuts (TSC) per Timestep (TS), %	Number of Outer Nonlinear Iterations, Newtonian Cycles (NC) per Timestep (TS)	Number of Solver Iterations (SI) per Newtonian Cycle (NC)
Acceptance Criteria	$\leq 1.0 \times 10^{-3}$	≤ 1.0	≤ 1.5	≤ 20

Step 7 defines an essential difference from previous works. Since we are dealing with a compositional simulation, the parameters involved are from a broader and more complex list. They are chosen in Step 7, with ranges picked from the reservoir engineer's experience. These same parameters are used in Step 8 for the sensitivity analysis and as input variables and optimization range in Step 9 for numerical tuning.

Several parameters from Table 2 in Step 7 are familiar to Black-Oil configuration for numerical solvers. The information below provides a better understanding of these parameters.

We focused exclusively on our chosen compositional solver parameters and in explaining their role. All ranges of the probability density function in the optimization were chosen based on the experience shared by reservoir engineers, scientists, and geoenvironmentalists.

- The maximum and minimum timestep size is included in Black-Oil solvers as well as normal variations in pressure and saturation. The maximum timestep size is the upper limit allowed through the solver iterations. Usually, it is set to be exactly at the timestep informed by a keyword of date or time from the simulation file. Whereas the minimum timestep size is the lower limit allowed through the solver iterations. If the simulator is at the minimum timestep size and, for some reason, the numerical solution does not converge, the simulation is suspended because the timestep size cannot be smaller than the minimum defined previously.
- Normal variation in global composition, on the other hand, is exclusive to the compositional solver. It specifies the typical changes in the composition's variables during a timestep.
- Maximum changes in pressure and saturation are in Black-Oil solvers. These changes identify the maximum changes in saturation and pressure through a timestep. If the change in normal variation is above that set by the maximum change, then, the timestep is cut to keep the changes defined by the normal variation.
- Maximum changes in global composition are exclusive to the compositional solver. This parameter specifies the maximum changes in

the global compositions during Newtonian iterations.

- The convergence of Newton's Method and Convergence Tolerance for Linear Solver are options in Black-Oil solvers too. It is used to define the convergence tolerance for the linear equation solver. The linear solver will stop if the condition specified by this keyword is satisfied. According to **Avansi et. al. (2019)** *"For simplicity of explanation, we consider a linear equation $Av = b$, and the root-mean-square (rms) residual is $r = b - Av$. Then, when $r(i)/r(0)$ for the n th iteration is less than the convergence tolerance, the criterion is matched and will move to the next iteration."*
- Threshold Adaptive Implicit Switching to water saturation or hydrocarbon global mole fractions is exclusive of the compositional solver. When this parameter is used, an explicit grid block is switched during the current timestep to implicit if changes in water saturation or hydrocarbon component global mole fractions in the block exceed their normal variation default value on saturation or a normal variation on composition. The verification is done after the timestep has converged.
- Maximum Number of Linear Iterations and Maximum Number of orthogonalization are parameters in Black-Oil solvers. This orthogonalization procedure is used to approximate factorizations and, then, accelerate the flow equations solver. It is important to note that this preconditioner is specific to the reservoir simulator used in our study.

From Table 1, it is possible to check the performance of the base model and verify the need to tune numerical parameters. Experience is crucial for choosing a practical Total MBE error, TSC/TS, NC/TS, and SI/NC acceptance criteria and the right choice of those filters to improve the tuning convergence and result.

They are included in the parameterization specific compositional numerical solver parameters, and these parameters are, then, run on sensitivity analysis and numerical tuning. The innovation from both previous studies is making compositional numerical tuning possible.

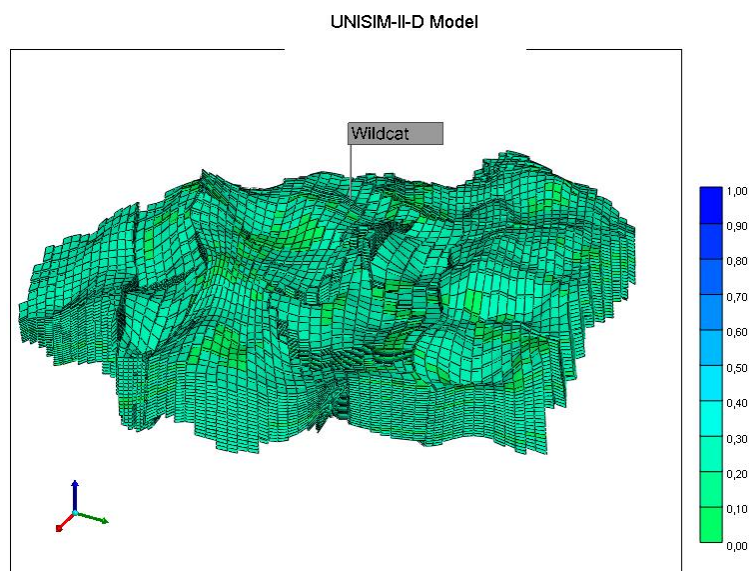


Figure 2. Overview of the model's water saturation.

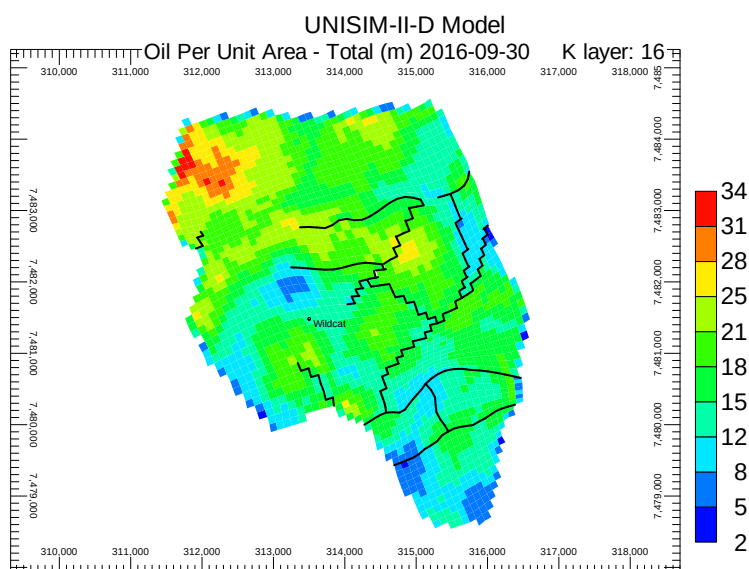


Figure 3. Overview of the model's quality map of the total mobile oil sum of all layers.

3. APPLICATION

The application considered a compositional case for WAG EOR, which resulted from the implementation of a production strategy in the UNISIM-II-D-CO Benchmark (Correia et al. 2015), shown in Figure 2.

The model's total mobile oil quality map is shown in Figure 3.

In the next step, the model received an injector and producer well pattern generated by the study of Camacho (2017). Figure 4 displays all wells from

the production strategy used in the proposed work.

The model's permeability from one layer is shown in Figure 5.

The model's porosity from one layer is shown in Figure 6.

The final application for validating this methodology is building risk curves that will use uncertainty levels and probabilities for reservoir and technical attributes, such as production system availability.

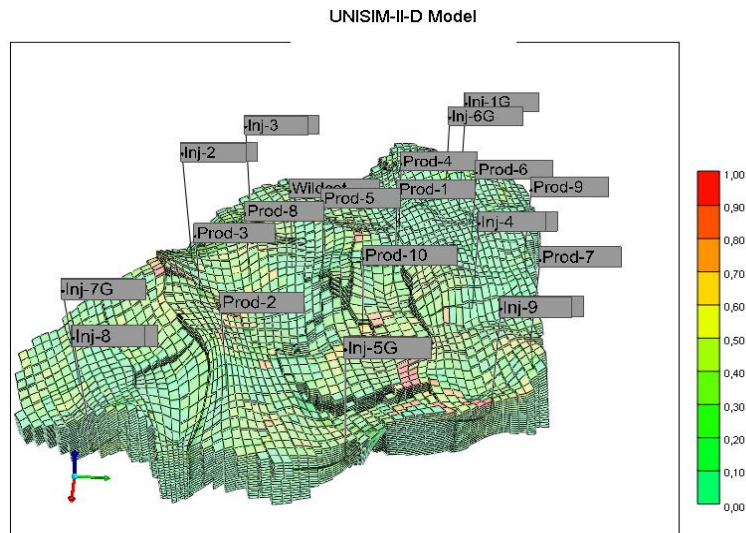


Figure 4. Injector and producer pattern imported for the WAG case – initial gas saturation distribution.

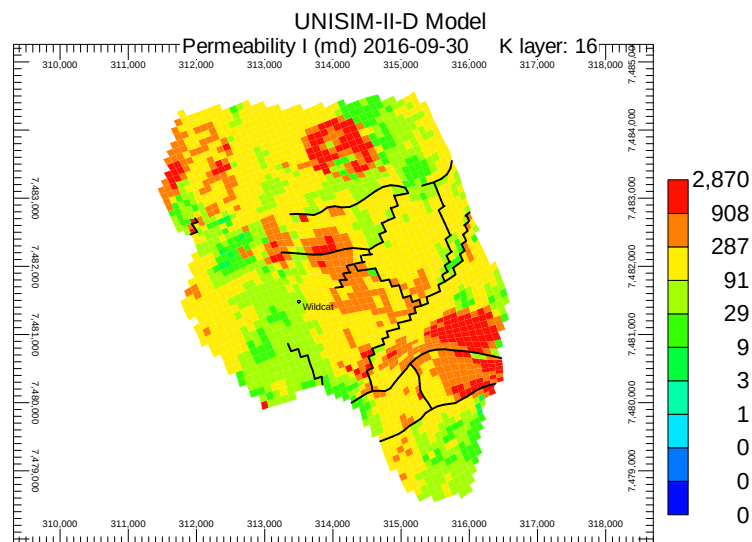


Figure 5. Sample of permeability distribution from one layer in the model.

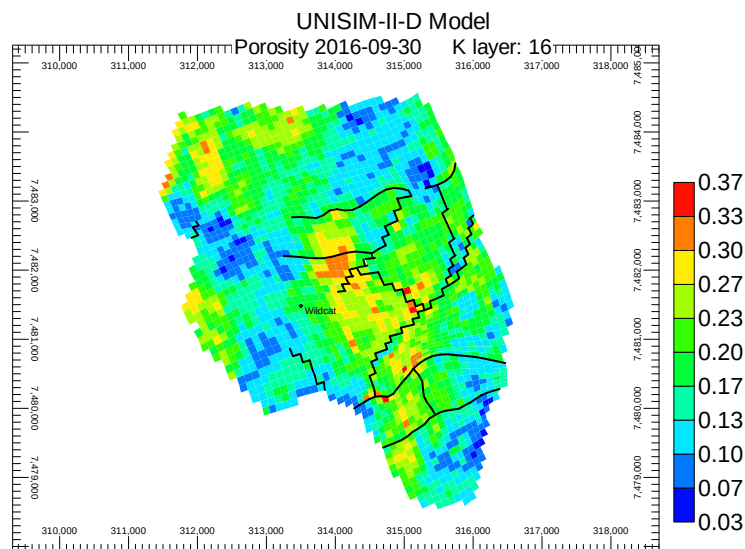


Figure 6. Sample of porosity distribution from one layer in the model.

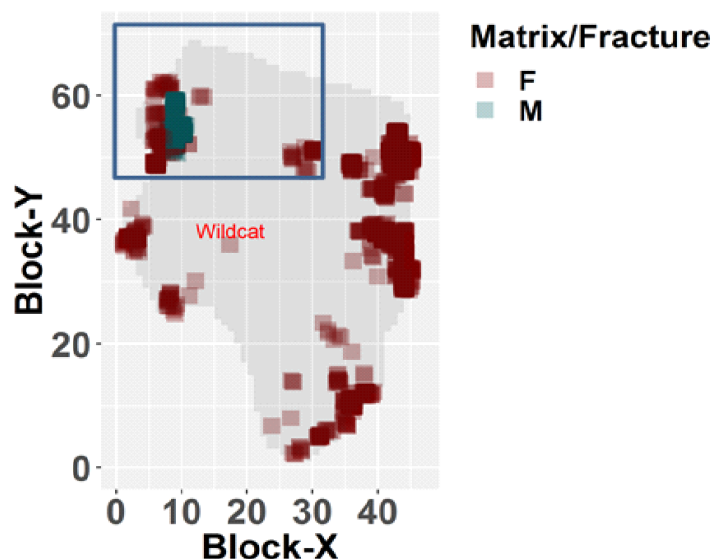


Figure 7. Spatial analysis of the convergence problem to build the submodel, selecting areas where the maximum number of cycles reached repeat timestep (without using the numerical tuning).

4. RESULTS AND DISCUSSION

Step 1 – Run base case simulation

The simulation model built is run to perform a diagnosis. It is essential to remember that, while our optimization case does not use automatic calibration, our target control comparative case is assumed to be the result of a single run with ADTSC automatic calibration with the default options of the commercial software.

Step 2 – Diagnostics of the numerical model

By verifying Table 1, the numbers for TSC/TS and NC/TS are inadequate and hinder model performance and, thus, justify the use of numerical tuning. The TSC/TS of 10.3 % is much higher than the acceptance criteria (less than or equal to 1.0), and the NC/TS of 2.0 is greater than 1.5.

Since the numerical model has the potential to improve the numerical performance, we move to the next stage.

Step 3 – Spatial analysis of the convergence problem

In this case, many convergence problems result in timestep cuts, located on either fracture or matrix. Therefore, the model must be subjected to a more rigorous numerical evaluation involving tuning. There is a high numerical error density on

reservoir borders. This is the criteria for picking a single submodel to cut in space and time the largest density of convergence problems from the base run. Also, this is the same submodel that will provide the optimized parameters after robust optimization for the entire set of models. The numerical parameters from optimizing the submodel are transferred back to the entire model and run again for consistency.

The base model simulated requires a long forecast period (10,957 days). We must check if it is possible to perform a model cut-out to create a submodel from the problematic reservoir regions highlighted in the previous step (Figure 4) to, in turn, perform a feasible numerical tuning. From the analysis of Figure 7, it is possible to obtain a submodel from the selection of a region where the most frequent timestep cuts occurred by exceeding the maximum variations defined in the simulator (numerical section). Figure 7 shows the red F blocks, which stand for fracture on blocks with converging problems, while the blue M blocks stand for matrix of blocks with convergence problems. Convergence problems are the occurrence of repeated timesteps.

Steps 4 and 5 – Submodel building

Figure 8 shows the entire reservoir simulation model before and after the submodel creation. This step is essential to decrease the execution time of the entire numerical optimization.

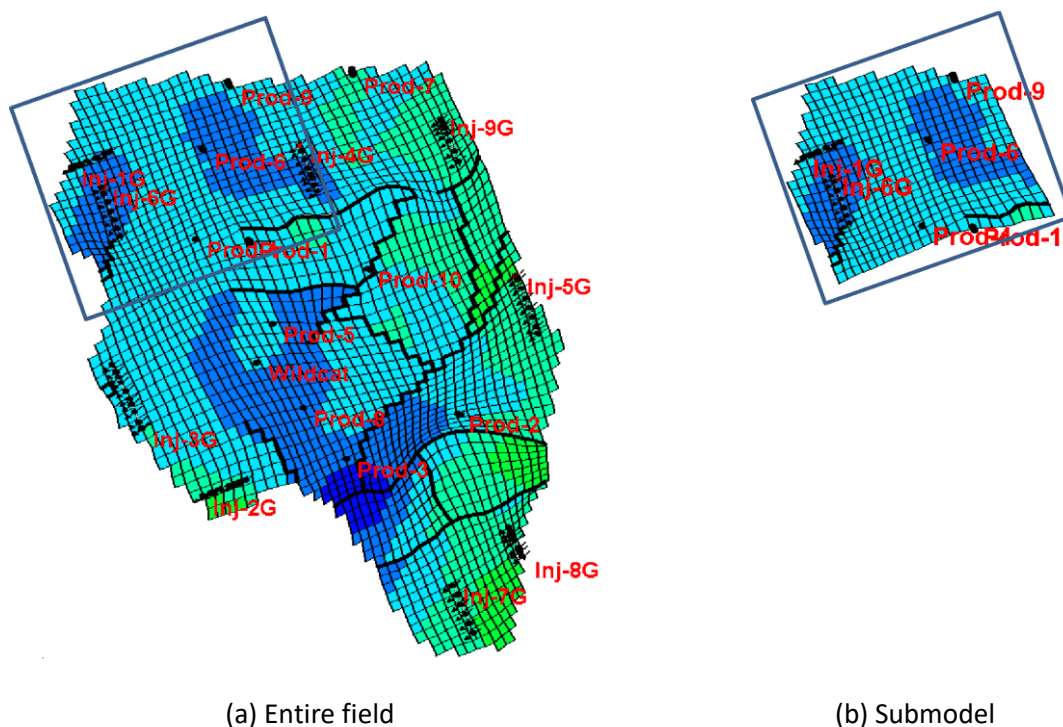


Figure 8. Building of submodel emphasizing producer and injector wells.

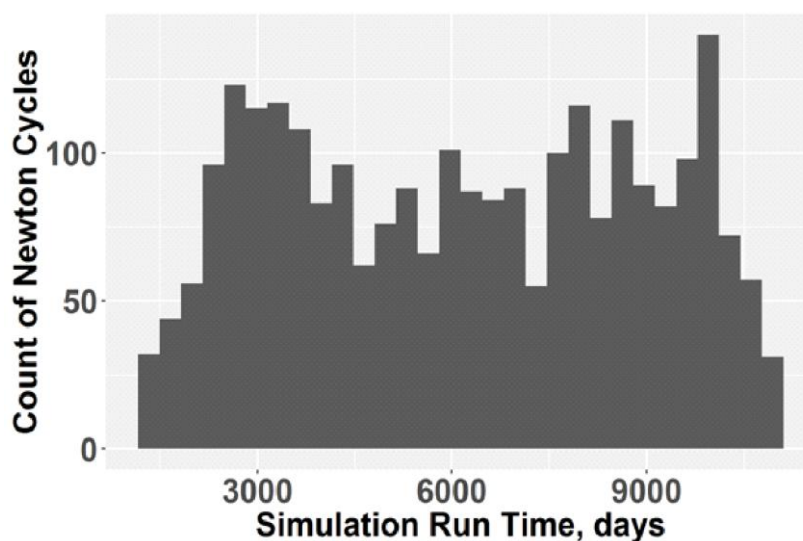


Figure 9. Histogram of the number of Newton cycles per simulation run time.

Step 6 – Cutoff simulation run time

Apart from evaluating the space, the Newton Cycles frequency is evaluated to check the convergence of the principal equations of the numerical reservoir model through the total simulation time (Figure 9).

From Figure 9, it is possible to observe that the number of occurrences of Newton cycles is quite uniformly distributed through the total simulation time, i.e., there is no characteristic frequency that helps us cut-off the simulation run time. As a result, it is not possible to reduce the simulation time during our numerical tuning.

Table 2. Numerical tuning parameterization (compositional parameters in red).

Parameter	Probability Distribution	Default Value	Probability Density Function (pdf)
Maximum Timestep Size, days	continuous (uniform)	365	$0, \quad x < 1$
			$1/(31-1), \quad 1 \leq x \leq 31$
			$0, \quad x > 31$
Minimum Timestep Size, days	constant	$\leq 1 \times 10^{-5}$	$\leq 1.0 \times 10^{-6}$
Normal Variation in Pressure per Timestep, kPa	continuous (uniform)	1,000	$0, \quad x < 300$
			$1/(2,500-300), \quad 300 \leq x \leq 2,500$
			$0, \quad x > 2,500$
Normal Variation in Saturation per Timestep, dimensionless	continuous (uniform)	0.15	$0, \quad x < 0.05$
			$1/(0.20-0.05), \quad 0.05 \leq x \leq 0.20$
			$0, \quad x > 0.20$
Normal Variation in Global Composition, dimensionless	continuous (uniform)	0.15	$0, \quad x < 0.03$
			$1/(0.15-0.03), \quad 0.03 \leq x \leq 0.15$
			$0, \quad x > 0.15$
Maximum Change in Pressure per Timestep, kPa	constant	10,000	1,000,000
Maximum Change in Saturation per Timestep, dimensionless	constant	0.5	0.95
Maximum Change in Global Composition, dimensionless	constant	0.5	0.95
Newton's Method Convergence, dimensionless	continuous (uniform)	0.001	$0, \quad x < 0.0001$
			$1/(0.0001-1.0000), \quad 0.0001 \leq x \leq 1.0000$
			$0, \quad x > 1.0000$
Convergence Tolerance for Linear Solver - Globally, dimensionless	continuous (uniform)	$\leq 5 \times 10^{-4}$	$0, \quad x < 0.00001$
			$1/(0.00001-0.001), \quad 0.00001 \leq x \leq 0.001$
			$0, \quad x > 0.001$
Threshold Adaptive-Implicit Switching to water saturation or hydrocarbon global mole fractions, dimensionless	constant	1.0	0.1
Maximum Number of Linear Iterations, dimensionless	constant	40	100
Maximum Number of Orthogonalizations, dimensionless	constant	80	200

Steps 7 and 8 – Numerical parameter definition and Sensitivity Analysis

Several parameters from Table 2 are familiar with the Black-Oil configuration for numerical solvers.

The numerical parameter optimization methodology employs all parameters as input; the computational time is then optimized through DECE optimizer (Yang et al., 2007), drawing candidate values and screening ranges of these parameters from step 7 to the best result of the

objective function (elapsed run time). There is one additional hard constraint on the optimizer related to the MBE: there is a maximum MBE error allowed for acceptable convergence of 1.0×10^{-3} . According to CMG CMOST user manual (CMG 2018), "The DECE optimization is an iterative optimization process that first applies a designed exploration stage and then a controlled evolution stage. In the exploration stage, the goal is to explore the search space in a designed random manner to get maximum information about the solution space. To do so, experimental design and

Tabu search techniques are applied to select parameter values and create representative simulation datasets. In the controlled evolution stage, statistical analyses are performed for the simulation results obtained in the designed exploration stage. Based on the analyses, the DECE algorithm scrutinizes every candidate value of each parameter to determine if there is a better chance to improve the solution quality if certain candidate values are rejected (banned) from being picked again. These rejected candidate values are remembered by the algorithm and they will not be used in the next controlled exploration stage. To minimize the possibility of being trapped in local minima, the DECE algorithm checks rejected candidate values from time to time to make sure previous rejection decisions are still valid. If the algorithm determines that certain rejection decisions are not valid, the rejection decisions are recalled and corresponding candidate values are used again."

The sensitivity analysis for the screening of optimization parameters was made through Plackett-Burman experimental design. Sensitivity analysis on this step serves to screen all variable and variable range effects on the simulator run elapsed time. Also, it serves to discard those variables without ANOVA statistical significance in the next optimization step, to reduce the number of runs on the optimization process, and increase the effectiveness of the process.

The sensitivity analysis was done for all the parameters above, but its result description does not need to be included because all the parameters analyzed influenced the optimization variables. Since the number of inputs is small, using all parameters simultaneously would not affect the optimization in any way, minimally raising the computational effort.

Step 9 – Numerical optimization, evolution, and results

The numerical optimization was done using the submodel described, considering:

- Base case: simulation model is run once with numerical parameters pre-defined by simulator with automatic tuning option activated. This implies that we are competing with the case where the GEM simulator allowed adaptable algorithms (ADTSC) to select the size of timestep and adjust numerical simulation parameters to improve the numerical performance done throughout the simulation shown in Figure 7 as a black triangle;
- Filtered: models selected from MBE error. Therefore, MBE error $\leq 1e-3$, shown in Figure 7 as orange circles;
- Selected (with and without filter): models selected with shorter elapsed time, with and without the MBE error filter, shown in Figure 7 as green squares and red diamonds.

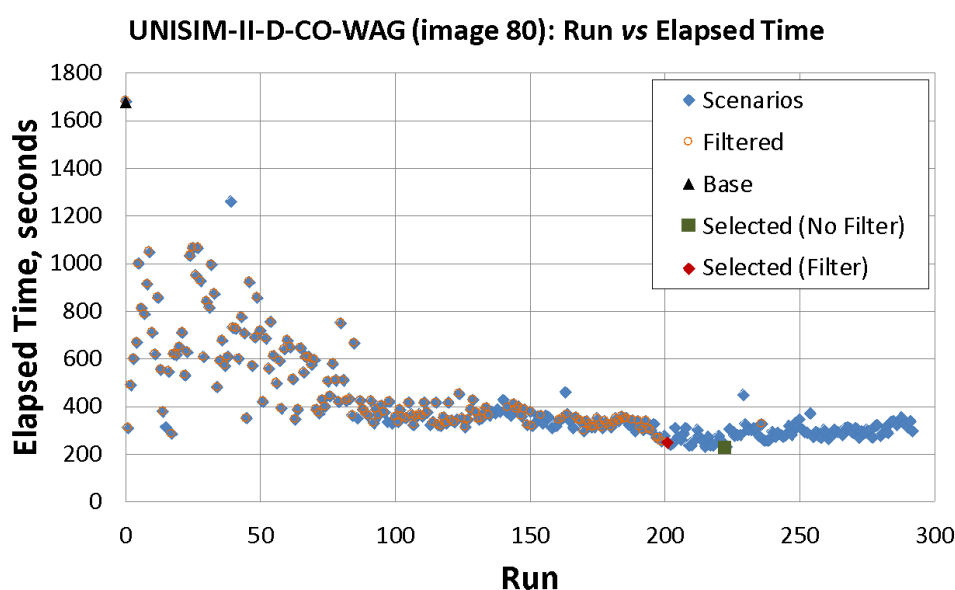


Figure 10. Results of numerical tuning for a single image.

Figure 10 displays the results of numerical tuning using the proposed submodel.

Table 3 shows the numerical optimization best parameter results for the best case, which is the red dot in Figure 7.

Step 10 – Numerical parameter consistency test

After the optimization step (using submodels) and the selection of numerical parameters from the filtering step, a consistency test was performed

for these same optimized numerical parameters, from what was optimized on the submodel, to run on the original model (without model cut-out) in local machines to ensure that the same computational conditions and bottlenecks are respected.

Results show that the default model using adaptive timestep control (keyword for numerical tuning using the commercial simulator) with a single run takes an elapsed time of 41,904 seconds (12 hours). While the calibrated model without automatic tuning and with our procedure takes an

Table 3. Numerical tuning optimization results for the best case (compositional parameters in red).

Parameter	Untuned Value	Tuned Value
Maximum Timestep Size, days	365	31
Minimum Timestep Size, days	$1 * 10^{-5}$	$1 * 10^{-6}$
Normal Variation in Pressure per Timestep, kPa	1000	1400
Normal Variation in Saturation per Timestep, dimensionless	0.15	0.1625
Normal Variation in Global Composition, dimensionless	0.15	0.06
Maximum Change in Pressure per Timestep, kPa	10000	1,000,000
Maximum Change in Saturation per Timestep, dimensionless	0.5	0.95
Maximum Change in Global Composition, dimensionless	0.5	0.95
Convergence of Newton's Method, dimensionless	0.001	1
Convergence Tolerance for Linear Solver - Globally, dimensionless	$5 * 10^{-4}$	0.001
Threshold Adaptive-Implicit Switching to water saturation or hydrocarbon global mole fractions, dimensionless	1.0	0.1
Maximum Number of Linear Iterations, dimensionless	40	100
Maximum Number of Orthogonalizations, dimensionless	80	200

Table 4. Risk analysis, uncertainty levels, and probabilities for technical attributes.

Attribute	Type	Levels (Probability)		
		0 (0.33)	1 (0.33)	2 (0.33)
System Availability	Platform	0.95	1.00	0.90
	Group	0.96	1.00	0.91
	Producer	0.96	1.00	0.91
	Injector	0.98	1.00	0.92

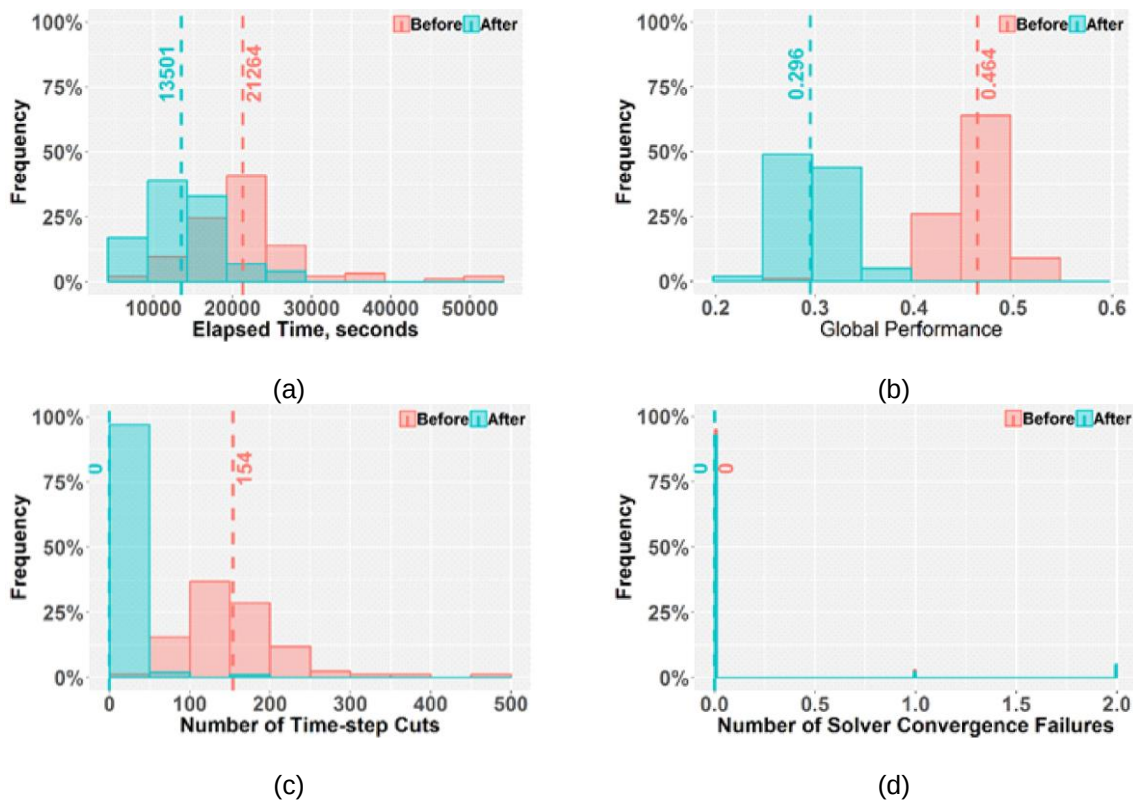


Figure 11. Step 11: Application – statistical analysis before and after the NT for 500 models.

elapsed time of 21,707 seconds (6 hours). That provides a time gain (default model) of about 48%.

Step 11 – Results of risk analysis application in terms of computational time

Five hundred models of the same reservoir were generated for risk analysis with the discrete Latin hypercube model based on the following

properties and technical attributes: First, system availability for the platform (Table 4), group of wells, producer, and injector wells. Secondly, in addition to system availability were included in the latin hypercube model generation continuous geological attributes, like rock compressibility (Table 5). Thirdly, discrete geological attributes (Table 6) were included, such as porosity and

Table 5. Risk analysis, uncertainty levels, and probabilities for continuous geological attributes.

Attribute	Unit	Probability Density Function (PDF)	
Rock compressibility (c_{fr}), (10^{-6})	(psi) ⁻¹	0,	$x < 19.5$
		$\frac{x - 19.5}{1163.7}$,	$19.5 \leq x \leq 57.1$
		$\frac{81.4 - x}{752.1}$,	$57.1 \leq x \leq 81.4$
		0,	$x > 81.4$

Table 6. Risk analysis, probabilities and uncertainty levels for discrete geological attributes.

Attribute	Levels (Probability)		
	0 (0.60)	1 (0.20)	2 (0.20)
Geostatistical Realization (Image)	500 equiprobable realizations		
Relative Permeability Curves	Kr0	Kr1	Kr2

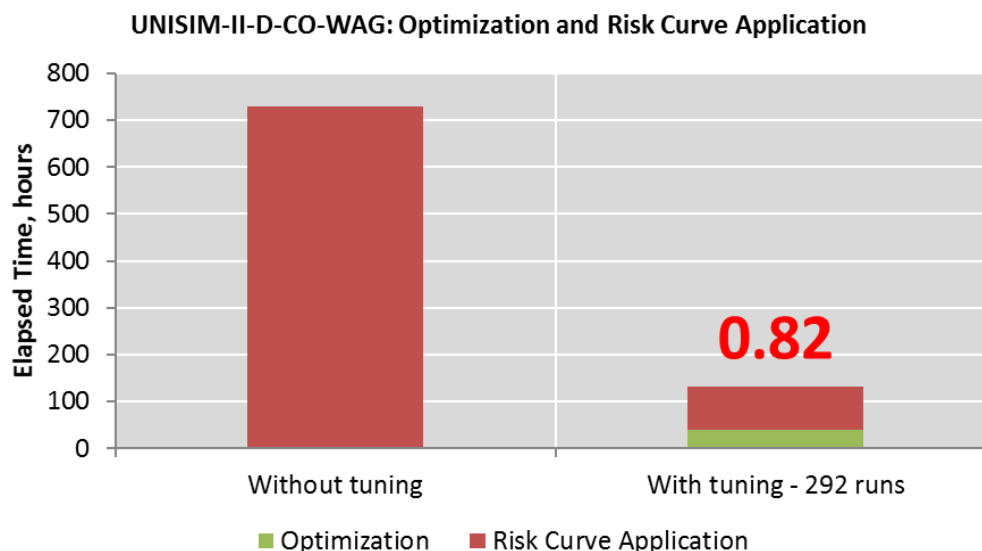


Figure 12. UNISIM-II-D-CO-WAG: briefing of application results.

permeability image realizations and relative permeability curves.

As illustrated in Figure 11a, there was an overall decrease in time for all realizations. Figure 11b shows an overall improvement in global performance. Figure 11c shows the near elimination of timestep cuts, and Figure 11d shows the elimination of solver convergence failures.

All 500 models were run and, as can be seen in Figure 12, an average 82% of computational time was saved. The previous simulation time (with 12 processors) was 729 hours and, after the tuning, this time fell to 132 hours, considering both the model training set of 292 runs plus the 500 models optimized runs, 40 hours for the procedure, and 92 hours for the ensemble run.

5. CONCLUSIONS

In this proposed manuscript, we discussed the improvements in the numerical modeling of compositional flow for a compositional simulation model of a type III carbonate reservoir, with a WAG injection scheme with total recycling of produced gas.

This improvement contribution provides a methodology with the capability to include both compositional and black-oil numerical solver parameters in every step of the numerical tuning

optimization for a broader and more robust model. The novelty of this work also lies in achieving good performance improvements for a complex compositional case study.

This methodology is straightforward, has a broader application, and is more comfortable to use even for geengineers with no reservoir simulation background. Employing submodels as a part of the methodology has proven useful for optimizing the numerical parameters of a compositional simulation model of a type III fractured carbonate reservoir, with the WAG injection scheme with total recycling of produced gas. From the submodel method, we achieved significant speedup gains since the single run of the base case simulation model was not accepted based on the defined criteria. Apart from this, it is simple and can be reproduced and applied to other simulation cases, showing the potential to reduce the daily computational effort of activities in reservoir engineering.

We were able to improve the numerical efficiency of compositional models in complex cases and achieve a comparable bulk gain in probabilistic risk analysis. The method considerably reduced the computational time spent on a compositional complex study.

The results of numerical optimization applied to a risk analysis study showed a remarkable amount of saved time obtained for five hundred simulation runs. The computational time saved is expected to

rise proportionally to new applications performed using the optimized case with more runs.

To conclude, we demonstrated that there are still shortcomings to simulator automatic numerical tuning routines. Simply using automatic calibration with default options hinder numerical performance, while our robust approach with no automatic routine offers more advantages. We can also conclude that the objective of this option in the commercial simulator is not to result in an optimization of a numerical model, but the improvement of the model's run time in comparison to the full default numerical one adopted by scientists and geoengineers, who may have no frequent contact with this option in the commercial simulator. This further emphasizes the importance of our methodology to obtain consistent and efficient models.

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6. REFERENCES

- Avansi, G., Rios, V., Schiozer, D. Numerical tuning in reservoir simulation: it is worth the effort in practical petroleum applications. **Journal of the Brazilian Society of Mechanical Sciences and Engineering**, p. 41- 59, 2019. <https://doi.org/10.1007/s40430-018-1559-9>
- Computer Modeling Group, CMG. (2018). CMG CMOST User Manual. Houston, TX, USA.
- Camacho, L. D. T.; **Methodology for the development of carbonate reservoirs with CO₂-WAG**. Master Dissertation. School of Mechanical Engineering – University of Campinas, Campinas, 2017.
- Card, C. C. H.; Kumar, A.; Close, J. C.; Kjosavik, A.; Agustsson, H.; Picone, M. M. A New and Practical Workflow for Large Multipad SAGD Simulation—An Oil-Sands Case Study. **Journal of Canadian Petroleum Technology**, v. 53(01), p. 14–31, 2014. <https://doi.org/10.2118/165511-PA>
- Correia, M. G.; Hohendorff Filho, J. C.; Gaspar, A. T.; Schiozer, D. J. UNISIM-II-D: Benchmark Case Proposal Based on a Carbonate Reservoir." Paper presented at the **SPE Latin American and Caribbean Petroleum Engineering Conference**, Quito, Ecuador, November 2015. <https://doi.org/10.2118/177140-MS>
- Li, H.; Yang, C.; Mirzabozorg, A.; Fedutenko, E.; Nghiem, L. X. Using Multiple Objective Optimization for SAGD Simulation Numerical Tuning. **SPE Heavy Oil Conference**, Society of Petroleum Engineers, Canada, 10 June 2014. <https://doi.org/10.2118/170024-MS>
- Rios, V. S.; Avansi, G. D.; Schiozer, D. J. Practical workflow to improve numerical performance in time-consuming reservoir simulation models using submodels and shorter period of time. **Journal of Petroleum Science and Engineering**, v. 95, p. 1-12, 2020. <https://doi.org/10.1016/j.petrol.2020.107547>
- Robinson, D. B.; Peng, D.-Y., The Characterization of the Heptanes and Heavier Fractions for the GPA Peng-Robinson Programs, Research Report (Gas Processors Association), Gas Processors Association, 1978.
- Robinson, D. B.; Peng, D. Y. A new two-constant Equation of State. **Industrial & Engineering Chemistry Fundamentals**, v. 15, p. 59-64, 1976. <https://doi.org/10.1021/i160057a011>
- Schiozer, D. J.; Santos, A. A.; Drumond, P. S. Integrated model based decision analysis in twelve steps applied to petroleum fields development and management. Paper presented at the **EUROPEC 2015**, Madrid, Spain, June 2015. <https://doi.org/10.2118/174370-MS>
- Yang, C.; Nghiem, L. X.; Card, C.; Breimeier, M. Reservoir Model Uncertainty Quantification Through Computer-Assisted History Matching. Paper presented at the **SPE Annual Technical Conference and Exhibition**, Anaheim, California, U.S.A., November 2007. <https://doi.org/10.2118/109825-MS>