12º CONGRESSO BRASILEIRO DE PESQUISA E DESENVOLVIMENTO EM PETRÓLEO E GÁS

TÍTULO DO TRABALHO:

HYPERTUNING FOR OPTIMIZATION METHODS USED IN FORWARD MODEL CALIBRATION

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Resumo

A utilização de técnicas de *Hypertuning* para encontrar a configuração ótima de um método de otimização faz-se necessária frente a complexidade no processo de calibração automatizada de modelos geológicos, na qual os otimizadores utilizados necessitam ser configurados para melhor se adequarem ao problema e assim atender as expectativas e gerar resultados mais fiéis. Este trabalho aplica técnicas de *Hypertuning* voltadas para definir o melhor conjunto de hiperparâmetros de um otimizador usado na calibração de Modelos Estratigráficos *Forward* (SFM) de reservatórios. Duas técnicas de *Hypertuning*, *Grid Search* e *Random Search,* foram aplicadas em um método de otimização meta-heurístico, *Particle Swarm Optimization* (PSO), usado na calibração de modelos SFM. Os resultados mostram que, quantitativamente e qualitativamente, o otimizador teve um melhor comportamento e gerou resultados de função objetivo melhores utilizando o conjunto de hiperparâmetros otimizado, quando comparado com um conjunto tido como ruim. Além disso, como esperado, em comparação com os valores padrão de hiperparâmetros recomendados pela biblioteca, os resultados não diferiram muito, apesar de ainda apresentar uma pequena melhora. Analisando os resultados de perfis de poços, é visto que as calibrações realizadas com a configuração ótima e por padrão do otimizador tiveram resultados semelhantes, tanto em questão de fácies das camadas estratigráficas, como na espessura dos modelos simulados em comparação com dados de referência, enquanto a calibração com uma configuração ruim obteve uma discrepância maior na espessura dos modelos.

Palavras-chave: *Hypertuning*, Modelagem Estratigráfica *Forward*, Calibração, Otimização.

Abstract

The use of Hypertuning techniques to find the optimal configuration of an optimization method is necessary given the complexity of the automated calibration process of geological models, in which the optimizers used need to be configured to better fit the problem, thus meeting expectations and generating more faithful results. This work applies optimization techniques aimed at defining the best set of hyperparameters for an optimizer used in the calibration of Stratigraphic Forward Models (SFM) of reservoirs. Two Hypertuning techniques, Grid Search and Random Search, were applied to a meta-heuristic optimization method, Particle Swarm Optimization (PSO), used in the calibration of SFM models. The results show that, mathematically, the optimizer performed better and produced better objective function results using the optimal set of hyperparameters found, compared to a set that was considered poor. However, when compared to the default hyperparameter values, the results did not differ much, although there was still a slight improvement. Looking at the results of the well profiles, it can be seen that the calibrations performed with the optimizer's optimal and default settings had similar results, both in terms of the facies of the stratigraphic layers and the thickness of the simulated models compared to the reference data, while the calibration with the poor setting had a greater discrepancy in the thickness of the models.

Keywords: Hypertuning, Stratigraphic Forward Modeling, Calibration, Optimization.

Introduction

In reservoir flow simulation, the geological model significantly influences the predictability behavior of the reservoir and its properties. With geological, production, and fluid data all in hand, engineers can develop different models that simulate the reservoir behavior to determine the best production strategy. Understanding the initial depositional environment and processes and their evolution is critical to effectively predict the spatial distribution and geometry of reservoir facies and permeability barriers (HUANG *et al.,* 2015). By constructing a good geological model of the basin, reservoir engineers can simulate flow with less uncertainty, resulting in a more accurate production simulation.

Stratigraphic Forward Modelling (SFM) is a technique that models the stratigraphic layers of a basin by reconstructing the geological processes and environmental conditions that may have occurred allowing the deposition of the original stratigraphic layers. The goal is to understand stratigraphic architecture through genetic processes rather than interpolation based on spatial statistics (TETZLAFF, 2023). Stratigraphic simulators aim to reproduce depositional sequences in sedimentary basins, by applying physical laws and equations that simulate deposition and other geological processes over time. However, the model validation with well data reveals discrepancies, that the application of calibration techniques can reduce. Automated calibration tools are mainly based on the minimization or maximization of an objective function, that compares the differences or similarities between the reference data and the model, using optimization methods to find the best combination of parameters that shows the best final model. Figure 1 shows how a geological reservoir model can be calibrated, starting with the creation of a conceptual model of the basin, and understanding the geological process and environmental conditions that allowed the deposition of such stratigraphic layers observed today. An initial model is created and so the calibration process starts with the optimization method searching for the best combination of parameters that will return the best model that matches the basin. Once the calibration tool reaches the stop criteria, the final model is found and quantified.

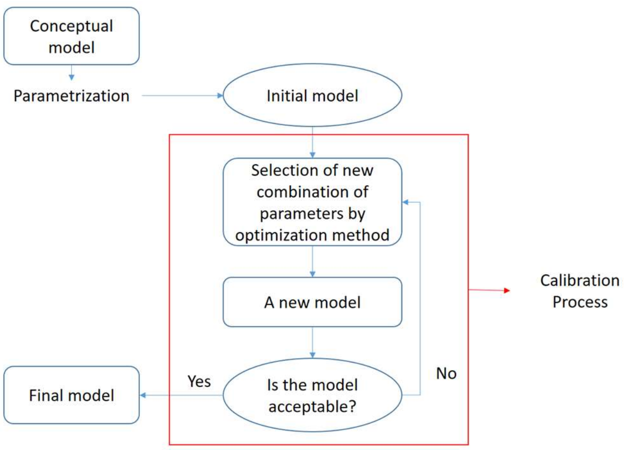

Figure 1 – Flowchart of a calibration process for geological reservoir models using optimization methods to search for the best combination of parameters.

The optimization methods search for the best combination of input data to simulate and find models more accurate with the reference data. Still, those methods use their internal parameters to configure their characteristics, called hyperparameters. These hyperparameters can be set for each problem and they can have a significant impact on the calibration process.

The search for the ideal configuration of hyperparameters for an optimization method requires scientific knowledge about the problem, intuition, and in some cases, trial and error (MANTOVANI *et al.*, 2023). The process called *Hyperparameter* or *Hypertuning* is the automated process of finding the optimal configuration of the optimizer that will make the method perform in the best way possible and will improve the calibration.

The objective of this work is to find the best combination of hyperparameters for the optimizer PSO (*Particle Swarm Optimization*) used to calibrate geological models in a calibration tool developed in the project involving the characterization and modeling of Morro do Chaves Formation (Sergipe Alagoas basin). The project contributed to the incorporation of stratigraphic modeling into the construction of reservoir models and improved their applicability by developing an automated calibration tool to improve the compatibility of the models created with the data observed in wells (BETTÚ *et al.*, 2022). During the Hypertuning process, two geological objective functions created in this project were used to quantify the results.

Methodology

There are a number of methods of applying Hypertuning that search for the best ensemble of hyperparameters. In this work, we will use the methods Grid Search and Random Search. Grid Search performs searching in a regular subset of data, in sequence, while Random Search combines selections randomly (PETRO *et al.*, 2019).

The internal parameters of PSO are ϕ_p (personal influence factor), ϕ_g (global influence factor), and ω (coefficient of inertia). These parameters influence the particle velocity and how the particles will search for the global optimal of the objective function used, following Equations 1 e 2, equation of particle velocity and position, respectively.

$$v_{ij}^{k} = \omega\left(v_{ij}\right)^{k-1} + \phi_p r_1\left[P - \left(x_{ij}\right)^{k-1}\right] + \phi_g r_2\left[G - \left(x_{ij}\right)^{k-1}\right] \tag{1}$$

$$x_{ij}^{k} = \left(x_{ij}\right)^{k-1} + \left(v_{ij}\right)^{k} \tag{2}$$

The variables x_{ij}^{k} and v_{ij}^{k} are the particle position and velocity, respectively, in the current step, while x_{ij}^{k-1} and v_{ij}^{k-1} are the position and velocity in the previous step. P and G are the minimum and maximum objective function values found in the current and previous step, respectively, and r_1 and r_2 are acceleration coefficients. The default value for these internal parameters of the PSO optimizer is 0.5 for each of them.

To use the Grid Search method, a total of five values were set for each PSO hyperparameter, all the same values for each. The method tests all possible combinations with the given values, in this case, a total of 125 different combinations. The values set for each hyperparameter are 0, 0.25, 0.50, 0.75, 1. In the case of Random Search, a limit was set for each hyperparameter, where the method randomly selects the combinations to be tested. For each hyperparameter, the limit was between 0 and 1. To compare the two methods, Random Search also tested a total of 125 different combinations.

The results were quantified by two different geological objective functions. The first one, SCOOF (*Stratigraphic Correlation Objective Function*), attempts to evaluate model fit by analyzing the similarity of facies found in the wells and the SFM models, capable of comparing facies successions of distinct sizes and resolutions (DUCROS *et al.*, 2023). Similarity is calculated by the difference or distance between simulated thicknesses and facies, from models, and interpreted thicknesses and facies, from well logs.

The second objective function, PROOF (*Probabilistic Objective Function*), evaluates the similarity between wells and SFM models by applying statistical techniques and hypothesis testing between the compared data, considering the probability that they belong to the same statistical population represented by a depositional sequence (BETTÚ *et al.*, 2022).

Results and Discussion

For each Hypertuning procedure, the 30% best and 30% worst results were analyzed. This means that out of all 125 calibrations performed in each method, for each objective function, the 38 best and 38 worst calibrations were analyzed. Figure 2 shows the comparison between the values of hyperparameters for both objective functions. It is observed that the behavior of the hyperparameters differs between the best and worst results.

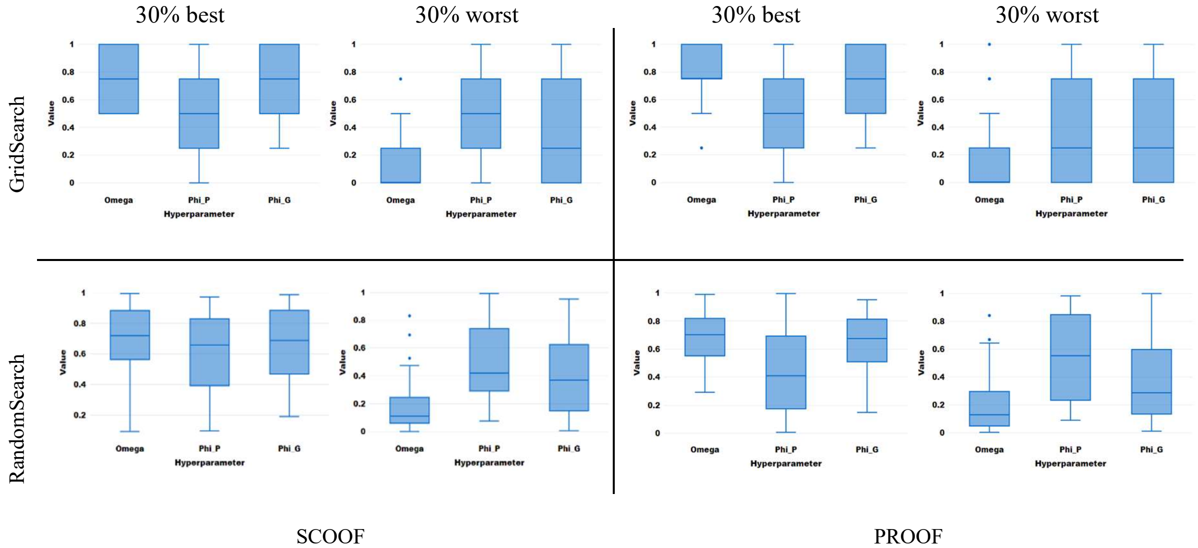

Figure 2 – 30% best and worst results for the hyperparameters found by the two methods, Grid Search and Random Search, using both objective functions.

Table 1 shows the values of the mean and the median for each hyperparameter, only for the results between the 30% of the best ones, found by SCOOF. For this type of problem, the Hypertuning process shows that we need to choose a value of ω greater than 0.5 and give more weight to the global influence factor ϕ_g.

Table 1 – Values of mean and median for each hyperparameter using both methods, Grid Search and Random Search, filtered by the 30% best results found using objective function SCOOF.

	Mean			Median		
	ω	ϕ_p	ϕ_g	ω	ϕ_p	ϕ_g
Grid Search	0.74	0.51	0.65	0.75	0.50	0.75
Random Search	0.68	0.60	0.67	0.72	0.65	0.68

Based on the results, the values 0.7, 0.55, and 0.65 for ω, ϕ_p, and ϕ_g, respectively, were chosen as the optimal combination of hyperparameters. These values were selected from the average between the mean results for each hyperparameter obtained for the two methods, shown in Table 1. The values 0.25, 1, and 0.25 were chosen as the worst combination. With the optimal, default, and worst combinations selected, three new calibrations were performed to compare the results by viewing and comparing the simulated wells to the observed wells. For these three configurations of hyperparameters, the model was calibrated with the same stop criteria and input data. Table 2 shows the results for these calibrations, for each objective function, respectively, with values of the objective function and values of the geological parameters calibrated (Carbo_Grains, Carbo_Mud, Carbo_Rud, Lutites, S1Supply, S2Supply, and Eustasy). It is observed that using SCOOF, the optimal combination chosen achieves a result very close to the default value of the hyperparameter while using PROOF the results vary more.

Table 2 – Calibration results for different combinations of hyperparameters chosen (optimal, default, and worst) using objective functions SCOOF and PROOF. Values of objective function and calibrated parameters.

SCOOF

	OF value	Carbo_Grains	Carbo_Mud	Carbo_Rud	Lutites	S1Supply	S2Supply	Eustasy
Optimal	39.157	0.500	0.500	0.500	0.500	0.500	1.153	1.500
Default	39.206	0.500	0.500	0.500	0.500	0.500	1.343	1.500
Worst	44.595	0.681	0.519	0.651	0.697	0.954	1.453	0.715

PROOF

	OF value	Carbo_Grains	Carbo_Mud	Carbo_Rud	Lutites	S1Supply	S2Supply	Eustasy
Optimal	0.325	0.500	0.500	0.500	0.607	0.586	0.677	0.500
Default	0.396	0.500	0.635	0.991	0.762	0.626	0.525	1.017
Worst	0.446	0.519	0.958	0.576	0.921	0.679	1.234	1.069

Figure 3 shows the facies logs for five wells used in the calibrations performed by SCOOF (left) and PROOF (right). Each color represents one different facies. It is observed that the different calibrations resulted in a very similar configuration of facies in wells. However, the calibrations with the optimal and default combinations of hyperparameters have better thickness adjustment.

The results in thickness adjustment can be seen and quantitively evaluated in all the calibrated wells. Table 3 shows that the optimal combination has resulted in a better approximation of thickness while the worst combination has resulted in a worse approximation, even if still improving, related to the initial model. These results highlight the potential of applying Hypertuning to geological modeling, where tuning the optimizer can produce models that are closer to reality in several ways.

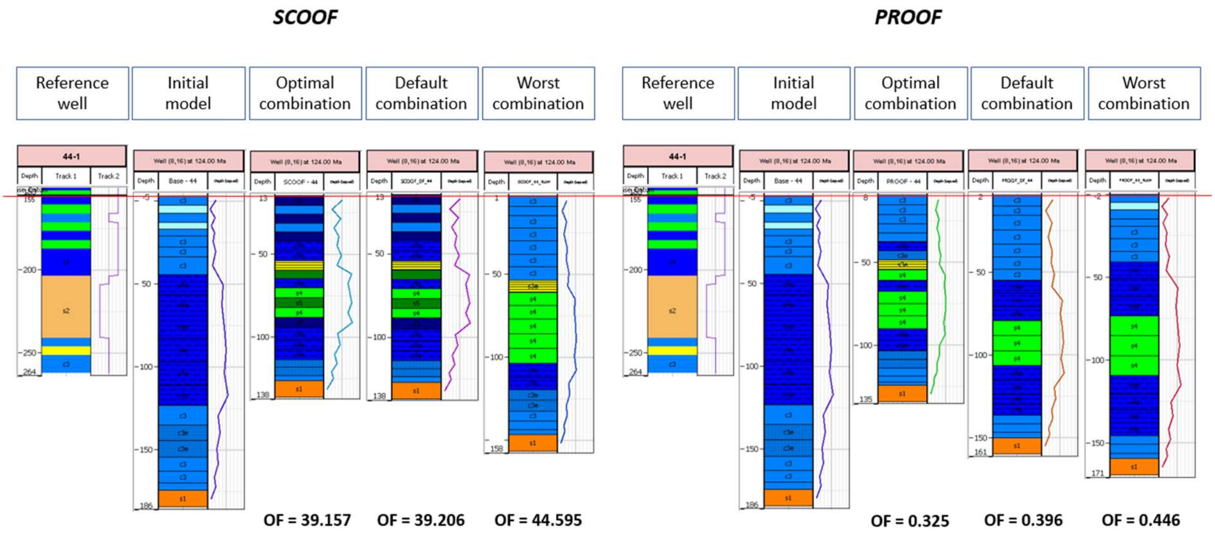

Figure 3 – Well log for reference, initial model, and calibrated wells. Results for SCOOF (left) and PROOF (right).

Table 3 – Thickness error for 5 wells calibrated using all three combinations of hyperparameters chosen for both objective functions (SCOOF and PROOF).

Well	Thickness error (%)						
		SCOOF			PROOF		
	Initial model	Optimal combination	Default combination	Worst combination	Optimal combination	Default combination	Worst combination
35	148.4	4.33	7.67	48.98	4.49	54.03	122.09
43	101.9	17.84	19.25	45.44	19.63	51.43	85.67
44	79.2	16.18	16.64	46.77	19.30	49.47	61.69
97	136.8	48.60	49.13	76.85	49.73	88.27	117.60
100	111.2	36.96	40.98	69.56	33.90	60.71	97.46

Figures 4 and 5 show the same results as the previous table, in terms of the thickness map for all the calibrations in comparison to the reference data, and a map of error for each model that was calculated as the difference between the model thickness and the reference thickness. All maps have units of meters. It seems that all three cases have improved the model thickness adjustment, with a good match to the reference thickness, but it is visible that using the optimal combination has resulted in a better approximation for both objective functions, while the default and worst combination have a better behavior with better result using the function SCOOF.

To complement the maps, we can analyze the improvement in model thickness using histograms. Figure 6 illustrates a reduction in thickness error in the calibrated models compared to the initial model when measured against the reference data. This is evident for both objective functions, as there's an increase in the frequency of thickness errors that are equal to or near zero.

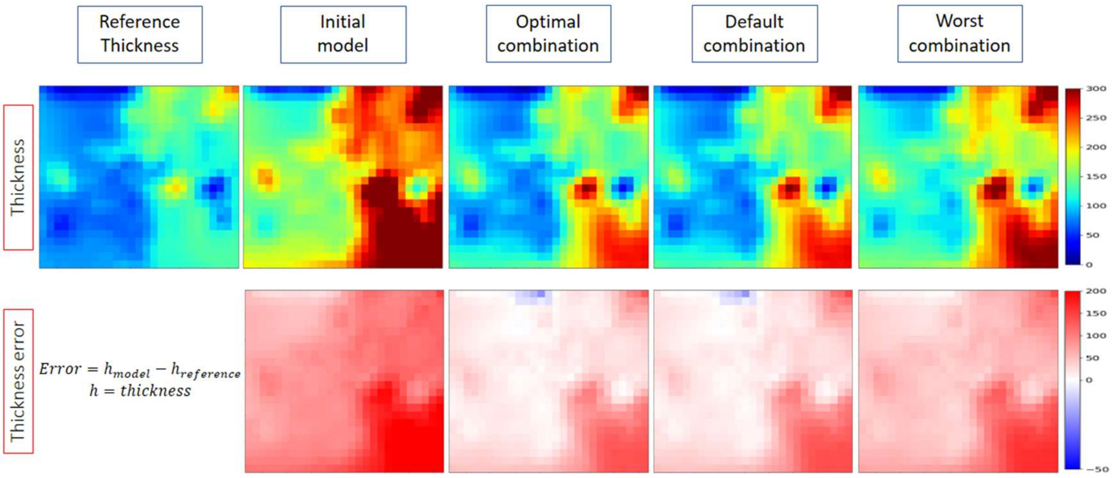

Figure 4 – Thickness for each model: reference, initial model, and calibrated models using objective function SCOOF, and the three configurations of hyperparameters set. The grids are 8400 x 7500 m.

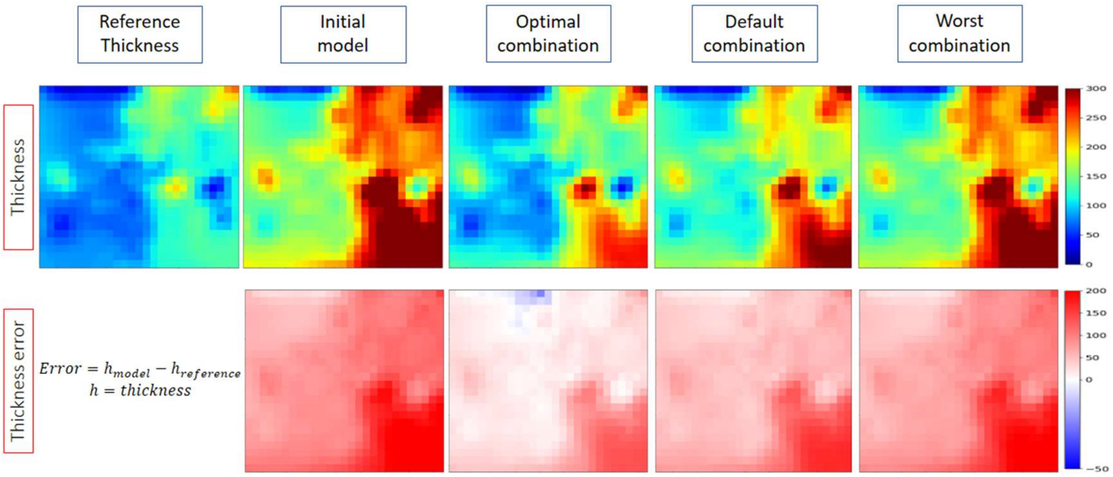

Figure 5 – Thickness for each model: reference, initial model, and calibrated models using objective function PROOF, and the three configurations of hyperparameters set. The grids are 8400 x 7500 m.

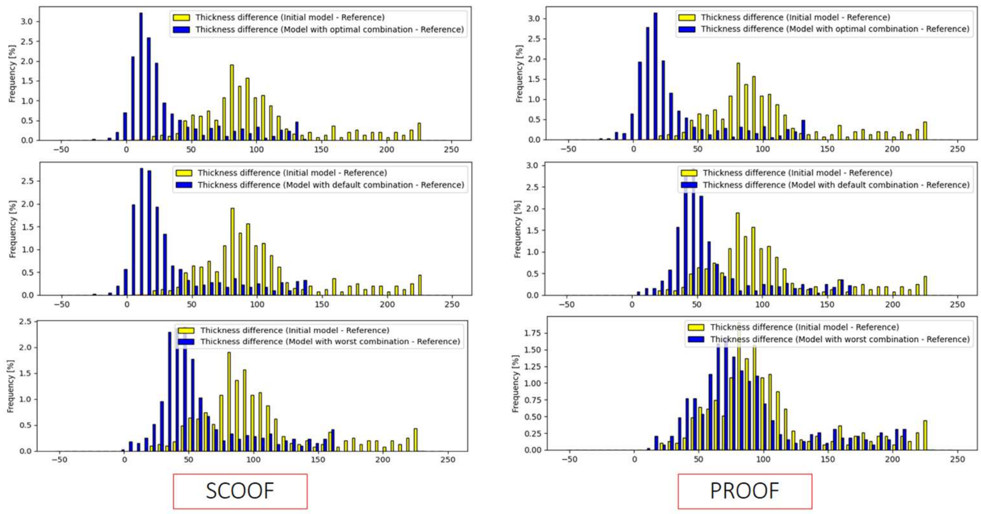

Figure 6 – Thickness error histograms per calibration.

Conclusions

The importance of Hypertuning lies in the ability to fine-tune the parameters of the optimizer to achieve more efficient performance and more accurate results, which is critical in the context of automated calibration of complex geological models. The results obtained in this work show that the calibrated models using the optimal and default configuration of hyperparameters reach similar results, in terms of facies definition and model thickness. It highlights the robustness of the default configuration of optimization methods, even if the optimal configuration shows a slight improvement, and shows the importance of Hypertuning, since improvements were obtained in all cases when the optimal configuration was used, and the methods used were easy to apply. The application of Hypertuning techniques, such as Grid Search and Random Search, is essential in the search for the ideal configuration of hyperparameters. Even if the improvements are subtle compared to the default configurations, the application of Hypertuning allows a more refined optimization adapted to the specifics of the geological problem in question.

Acknowledgments

We would like to thank the Santa Catarina State University-UDESC for the opportunity provided through the scientific initiation scholarships and Beicip-Franlab for granting us acess to OpenFlow Suite academic licenses.

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