Improved Surface-Subsurface Coupled Reservoir Simulation using Automatic PID Control ⋆

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Abstract: A PID control scheme has been developed to reduce both non-physical oscillations and computational effort in coupled surface-subsurface simulation. It is shown that the employed control scheme selects superior time steps as compared to a commercial off-the-shelf coupling software (with respect to computational efficiency). Our methods include a novel implementation of a time stepping algorithm in a PID framework. The PID controlled simulation was 297% faster than the default simulation, and incurred less than 0.5% error in production profiles. The control scheme developed can be applied to any commercial simulator where the user can select the time step, without alterations to underlying code.

Keywords: Reservoir Simulation; Surface-Subsurface Coupling; PID Control; Time Stepping; Integrated Oil Reservoir Modeling; Production Optimization, Integrated Operations.

1. INTRODUCTION

Reservoir and surface network coupling is a well-defined problem in offshore asset simulation. Surface facilities, wells, and reservoirs all impose disparate boundary conditions on one another. Therefore, it is critical that these systems are successfully modeled in simulation to best design and forecast offshore projects. Coupling is the process of simulating physically disparate assets as one system in order to determine overall project performance (IP, EUR, etc.). This involves, as depicted in Fig. 1, the reservoir (subsurface) and the surface network (well, pipeline, separators, valves, etc.). Coupling methods fall into three categories: explicit, partially implicit, and fully implicit. The categories span from the simplest method (explicit coupling), where two independent software packages share information at the point of coupling, to increasingly convoluted and computationally expensive methods. For example, the fully implicit coupling method requires all solutions of the reservoir and surface network mass balances to converge simultaneously, via a single software package.

The more complex methods provide accurate results; however, they require additional computational effort and are expensive to design. Fig. 2 depicts the relationship between solution accuracy and computational effort that exists in the primary coupling schemes. Evidence suggests that the partially implicit method balances speed and accuracy most effectively.

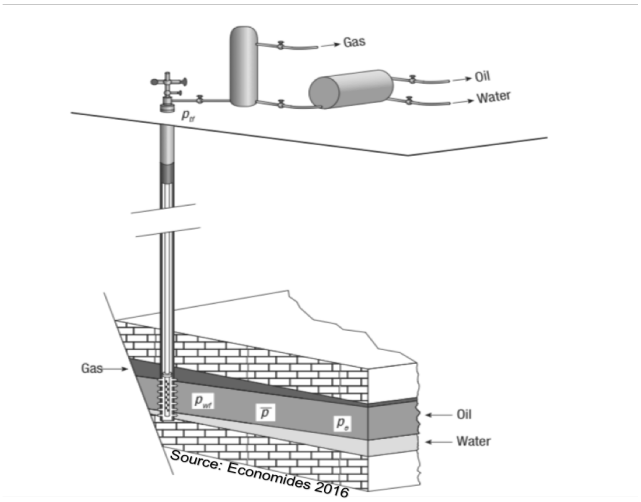

Fig. 1. Surface-Subsurface system

The study of coupling began with Dempsey et al.'s (1971) nascent coupling scheme proposals. Early proposals were typically explicit or partially implicit, as early computers could not solve large, fully implicit systems. Emanuel et al. (1981) and Startzman et al. (1977) improved upon earlier work by testing partially implicit coupling in a three-phase reservoir, with the use of a middle time step pressure as a means to improve the well deliverability curve across the time step. Litvak et al. (1995) successfully implemented various coupling schemes in commercial software. Byer et al. (1998) utilized preconditioned Newton methods to improve surface-subsurface coupling. Hegpuler et al. (1997) coupled multiple reservoirs to a central production facility and included injection support in simulation.

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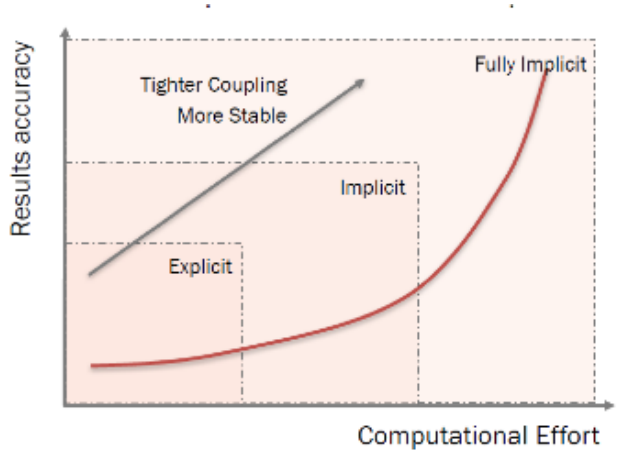

Fig. 2. Solution method computational effort

Coats et al. (2003) implemented well domain decomposition to enhance coupling. Guyaguler et al. (2011) built the Field Management framework with Schlumberger's INTERSECT and PIPESIM. Mengdi (2014) tested Schlumberger's INTERSECT and PIPESIM's partially implicit ("iteratively lagged") coupling scheme and found that simulated production profiles matched well with a fully implicit coupled system in MRST. Cao et al. (2015) provides a comprehensive overview of modern coupling methods.

The use of PID controlled adaptive time stepping in numerical simulation is well established. Early work, Gustafsson et al. (1988), included the use of automatic control to perform numerical integration of ODE's. Hairer et al. (1996) described the use of PID control in time stepping problems, and Valli et al. (2002) utilized PID time step control in the simulation of a 2D coupled viscous flow and heat transfer problem. However, automatic control applications in oil and gas have been limited. Akakpo et al. (2017) used automatic PID control to optimize time stepping in reservoir simulation. Despite prior successes, automatic control has not previously been used to perform adaptive time stepping in coupled surface-subsurface simulations.

We hypothesized that by controlling coupling error, oscillations in coupled simulation would diminish. We postulated that manipulating time step size via a PID controller could be used to control coupling error. To this end, we designed a partially implicit coupling solution that reduces oscillation, as well as computational effort, and can be implemented in any coupling program where the user can alter the time step. Our time step selection scheme executes small time steps during periods of significant transient pressure, and optimizes time steps in steady-state pressure conditions by selecting the largest time step that avoids oscillation.

This paper is organized in 8 sections. Section 2 describes in detail the primary coupling mechanisms and their associated benefits and pitfalls. Section 3 and 4 introduces coupling error and the PID controller derivation. Section 5 describes the underlying simulation as well as the control loop. In section 6 and 7, we validate our hypotheses by showing a case study with a simple reservoir and network in Schlumberger's INTERSECT and PIPESIM.

2. COUPLING SURFACE AND SUBSURFACE

In explicit coupling, a set of separate simulators (e.g. a standalone reservoir simulator package and a standalone network multi-phase flow simulator package) are utilized. During simulation, the independent simulations are solved sequentially at equivalent time steps. At the beginning of each time step, the network simulator will typically pass its previously calculated solution for the bottom hole pressure to the reservoir simulator. The reservoir simulator assimilates this value, and uses it as a boundary condition for the duration of the time step, i.e., $t+\triangle t$. However, well models in reservoir simulation are based upon steady state radial flow, i.e. the Peaceman Equation as determined by Peaceman (1978). Therefore, the IPR calculations assume that the pressure in the completed grid block remains constant across $t+\triangle t$: this is the so-called steady-state IPR. For short periods of transient pressure behavior in the reservoir, the steady-state simulated IPR does not accurately capture well performance. That is, the simulation assumes a steady-state IPR, when in fact the completed grid block pressure changes significantly. The IPR is in effect overestimated during the simulation, and results in pressures and rates that exceed real, transient production. During the next time step, the reservoir simulator responds to the earlier, large IPR by drastically reducing the pressures in the completed grid block and surrounding grid blocks. The new, reduced IPR curve yields a drastically smaller production rate and pressure. This cycle repeats itself during periods of pressure transience. Thus, the explicit method is almost always unstable. These cycles are referred to non-physical oscillations in coupling terminology. Fully implicit coupling treats the reservoir, well and surface facilities as one system of equations. Although such schemes eliminate non-physical oscillations, fully implicit schemes have high development costs and are computationally expensive. Like explicitly coupled systems, partially implicit coupled systems utilize separate surface and subsurface simulators. However, partially implicit coupled simulations employ algorithms to promote boundary condition agreement between the simulators at each time step. Typically, boundary properties (bottom hole pressure, etc.) are iteratively passed between the simulators multiple times during Newton-Raphson iterations, at each time step. This process is repeated until both simulators converge within a specified tolerance. While researchers have been successful in finding partially implicit coupled system solution schemes, these solutions are often computationally expensive and apply to specific software packages or propose adjustments that must be made to underlying simulator code. See Schlumberger's INTERSECT manual for additional details on this coupling method. In addition, partially implicit simulations are still prone to non-physical oscillation. Zhang et al. (2017) provides a succinct explanation of non-physical oscillations.

3. CONTROLLED VARIABLE IN TIME STEPPING

In this section, a typical step size selection scheme used for the numerical integration of ODEs is introduced. All concepts are taken from Gustafsson et al. (1988). By analogy, we have used the following to consider coupling error.

Given a method of order p, local error r varies asymptotically with step size h such that $r \sim h^{p+1}$. If we consider that

$$r = \phi h^{p+1}, \tag{1}$$

where ϕ is the coefficient vector that is a function of the solution of the differential equation. ϕ is O(1) as $h \rightarrow 0$. If the user specifies an error tolerance, *tol*, h can be maximized while obeying the tolerance

$$\frac{\|r\|}{h} = tol, \tag{2}$$

where $\|r\|$ is the norm of the error. The subsequent step h_{n+1} should then be selected such that

$$h_{n+1} = \theta h_n, \tag{3}$$

where

$$\theta = \left(\frac{tol}{\|r_n\|/h_n}\right)^{1/p}. \tag{4}$$

Similar time step size selection criteria were utilized by Jensen (1980) in reservoir simulation. In coupled simulation, non-physical oscillations are a direct result of error between the respective surface and reservoir simulator solutions. In our experiments, coupling error, e_c, is a scalar and is defined as

$$e_c = r = \frac{PWH_{reservoir} - PWH_{surface\ network}}{PWH_{reservoir}}. \tag{5}$$

In (5), PWH is the well head pressure, determined at time step n, by the reservoir simulator and surface network simulator, respectively. These pressure values represent the coupling point. The bottom hole is also an acceptable choice. We re-label e_c as r_n: the coupling error associated with time step n. (3) causes oscillations for many differential equations and integration methods. Gustafsson et al. (1988) employed automatic control to fix that problem.

4. CONTROL PERSPECTIVE AND PID CONTROL

The following section introduces the general control loop used by Gustafsson et al. (1988). The PID controller used in coupling will be derived. The derivation is based upon work done by Soderlind et al. (2006) and Akakpo et al. (2017). It should be noted that the controller was derived to stabilize and partially reduce error, yielding a smooth response. Total elimination of error would result in a prohibitive number of time steps. Fig. 3 illustrates the general closed-loop control scheme. G_p consists of the differential equations and the integration scheme. It is nonlinear and is a function of time. G_c consists of the step size controller. If we consider that the logarithm of h to be the plant input, then the nonlinearity in (3) becomes an affine relationship. We can express $log(h_{n+1})$ in terms of $log(h_n)$ by referencing (4). Manipulation of (3) and (4) yields

$$log(h_{n+1}) = log(h_n) + \frac{1}{p}(log(tol) - log(\frac{\|r_n\|}{h_n})). \tag{6}$$

In Fig. 3, *tol* is the set-point (user defined tolerance for error), and the step size is the manipulated variable. In addition, control error can now be defined as

$$e = log(tol) - log(r_n). \tag{7}$$

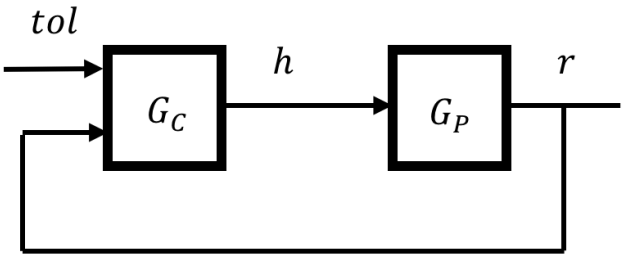

Fig. 3. General step size closed-loop control scheme

So far we have illustrated the basis for how error and control can be applied to time stepping. The following derivation is based upon work done by Akakpo et al. (2017). Fig. 3 serves as an appropriate control loop reference for the following. We first consider the following classic PID controller and associated transfer function, respectively:

$$u(t) = K_p * e(t) + K_i * \int e\,(t) + K_d * \frac{\partial e}{\partial t}, \tag{8}$$

$$G_{PID} = \frac{K_i + K_p s + K_d s^2}{s^2}. \tag{9}$$

We employed the following backward shift operator to achieve a discretized controller at time step n:

$$q^{-1} * u_n = u_{n-1}. \tag{10}$$

As a note, $u_n - u_{n-1} = \bigtriangledown f$. We applied (10) to (8) and obtained:

$$u_n = e_n[K_p + \frac{q-1}{q} * K_d + \frac{q}{q-1} * K_i]. \tag{11}$$

After we applied the backshift operator to error we obtained

$$e_n = q^{-1}[log(tol) - log(r_n)], \tag{12}$$

and by substituting $u_n = log(h_n)$, we obtained

$$C^{PID}(q) = q^{-1}(K_p + \frac{q-1}{q} * K_d + \frac{q}{q-1} * K_i). \tag{13}$$

Further substitution yields

$$log(h_n) = C^{PID}(q)[log(tol) - log(r_n]. \tag{14}$$

By substituting the backward shift operator, $\bigtriangledown = \frac{q-1}{q}$, we obtained:

$$\triangle log(h) = (K_p \bigtriangledown + K_d \bigtriangledown^2 + K_i)[log(tol) - log(r)]. \tag{15}$$

This is equivalent to the recursion:

$$\begin{aligned} log(h_{n+1}) - log(h_n) = {} & K_I(log(tol) - log(r_n)) \\ & - K_p(log(r_n) - log(r_{n-1})) \\ & - K_D(log(r_n) - 2log(r_{n-1}) \\ & + log(r_{n-2})). \end{aligned} \tag{16}$$

After rearranging to simplify log operators we obtained:

$$log(\frac{h_{n+1}}{h_n}) = K_I log(\frac{tol}{r_n}) - K_P log(\frac{r_n}{r_{n-1}}) - K_D log(\frac{r_n r_{n-2}}{r_{n-1}^2}). \tag{17}$$

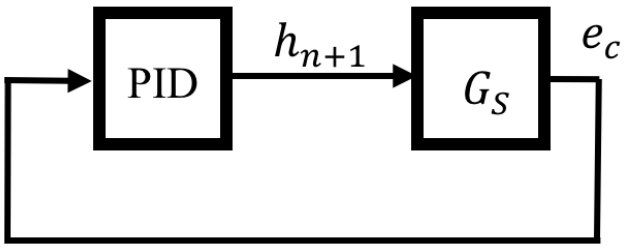

Fig. 4. Coupling closed-loop control scheme

After applying the exponential, we derived our final PID controller in the time domain:

$$h_{n+1} = h_n * (\frac{tol}{r_n})K_I * (\frac{r_{n-1}}{r_n})^{K_P} * (\frac{r_{n-1}^2}{r_n * r_{n-2}})^{K_D}. \quad (18)$$

5. EXPERIMENTAL COUPLING CONTROL LOOP

In this section, the experimental surface-subsurface coupling control loop will be discussed. In addition, the underlying commercial simulators and simulation settings will be discussed. Fig. 4 illustrates the control loop in our experiments. Prior to executing the loop, the coupled simulation is initialized with a small set of time steps. After the coupled simulator advances one time step, the coupling error (5) from the time step is passed to the PID controller (18) to determine the next optimal time step. This PID controller calculated time step is then executed by the coupled simulation, G_S, and the process is repeated until the simulation is finished. Schlumberger's INTERSECT (IX) with PIPESIM (2016) was used to perform the coupled simulation. The Field Management (FM) suite of algorithms were employed to perform the coupling. The partially implicit coupling solution method was selected. The field tested featured a single producer, PROD1. PROD2 was left shut-in. Three water injection wells (IW1, IW2, IW3) and two gas injection wells (IG1, IG2) supported PROD 1. Bottom hole pressure was unconstrained, while production and injection rates were constrained. Fig. 5 illustrates the PIPESIM network used in the coupled simulation. PIPESIM's black oil model was utilized, and sink GATHER operated at a constant 300 PSIA. Both the reservoir and surface models were created by Schlumberger for our purposes. The reservoir had 100 mD, 100 mD and 10 mD permeability in the (i, j, k), respectively. Each grid block was 250 ft X 250 ft X 10 ft, and the grid was 10X10X12.

6. RESULTS: REDUCTION OF OSCILLATIONS

This section includes results which illustrate our automatic control scheme's ability to reduce coupling error and non-physical oscillations. Initially, we tested our controller's effectiveness in IX and FM's relaxed coupling setting (IX/FM). By relaxing simulation thresholds, which IX and FM consider when initiating a time step, the coupled simulation yields significant coupling error and oscillation. We selected a *tol* of 1, and utilized gains empirically determined by Moller (2014) for PID controlled adaptive time stepping in a transient heat transfer problem. Figs. 6 and 7 highlight results from our experiment. Fig. 6 illustrates our controller's ability to reduce error as compared to the

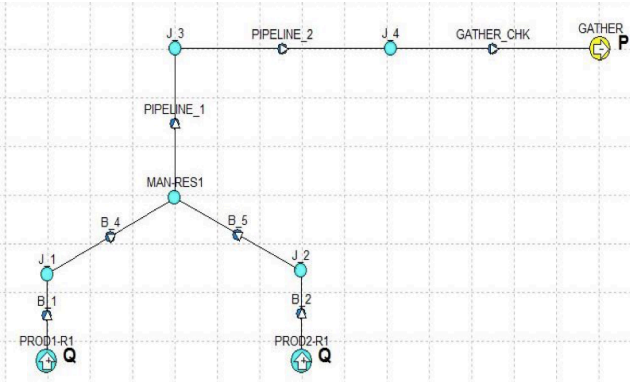

Fig. 5. PIPESIM surface configuration

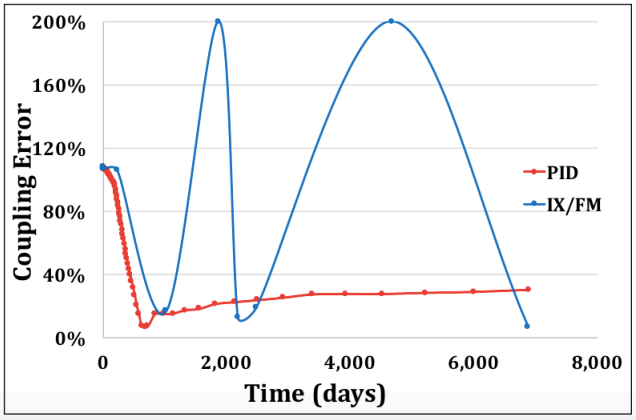

Fig. 6. Coupling error oscillation reduction

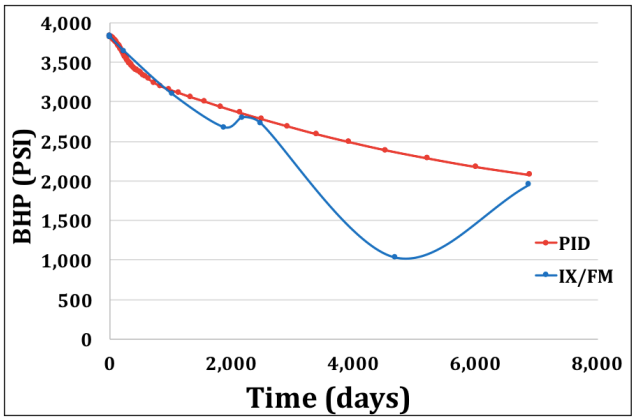

Fig. 7. Bottom hole pressure oscillation reduction

IX/FM relaxed settings. The blue curve illustrates the oscillatory coupling error of the relaxed IX/FM simulation. The red curve illustrates the PID controlled simulation. The oscillation (overshoot) is due to increased contribution of integral control. Equation (18) also illustrates how integral control dominates as error stabilizes. Fig. 7 illustrates the non-physical bottom hole pressure (BHP) decline in the IX/FM simulation, as compared to the realistic BHP decline achieved in the PID controlled simulation.

7. COMPARSION TO STANDARD STRATEGIES

This section compares our PID control scheme to Schlumberger's default coupling settings in FM's iteratively

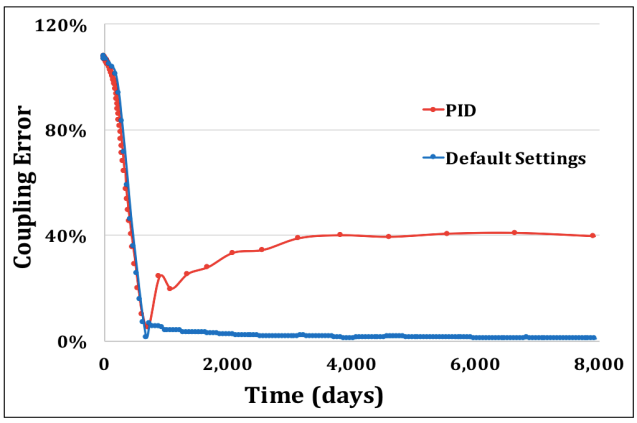

Fig. 8. Coupling error in modified Moller PID/ default

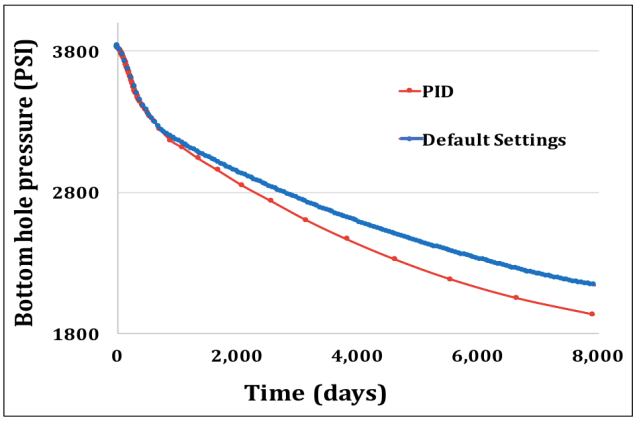

Fig. 9. BHP in modified Moller PID/ default

lagged scheme. Thus, we compare our solution against a current industry standard coupling solution. Two gain settings are tested here. A modified Moller ($K_p = 0.1$) and a scheduled gain controller highlight the success of PID control in coupling. Figs. 8 and 9 illustrate error and pressure profiles in the modified Moller and default Schlumberger coupling settings. It is clear that the PID controller does not reduce error as effectively as Schlumberger's default settings. In addition, there are discrepancies between the PID and default pressure profiles. However, the PID controlled simulation executed 62 time steps, while the default simulation executed 162 time steps. The PID controlled simulation is 45% faster than Schlumberger's default. Fig. 10 depicts cumulative production for both cases, and illustrates that the PID simulation only incurs 0.8% error with respect to the default simulation's cumulative production. Therefore, it can be argued that the PID controlled simulation is superior in efficiency (reduced computational effort), and is accurate in forecasting model performance. Figs. 12 through 14 illustrate our scheduled gain controller results. Gains were manually evaluated and optimized at each time step. Fig. 11 details the gain schedule. This PID controller executed 19 time steps, while the default simulation executed 146. The PID controlled simulation took 16.9s to complete, while the default simulation took 50.2s to complete. Therefore, the scheduled PID simulation was 297% faster, while incurring less than 0.5% error in cumulative production.

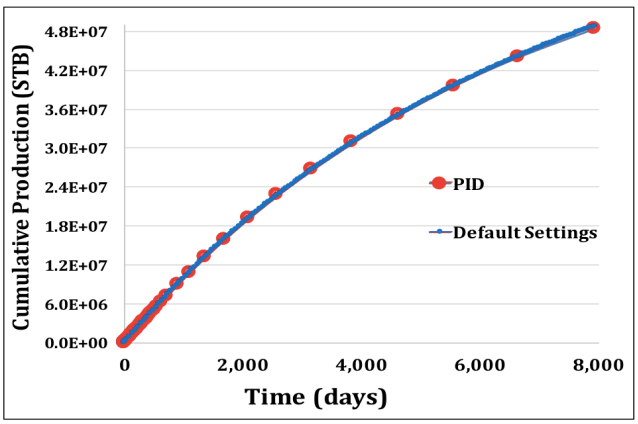

Fig. 10. Cumulative production in modified Moller PID/ default

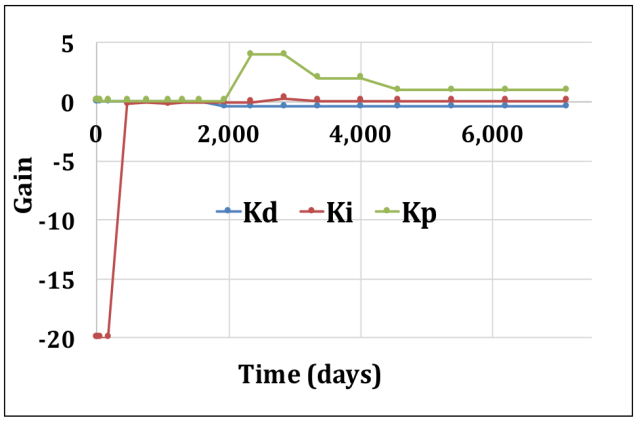

Fig. 11. Gain schedule for PID controller

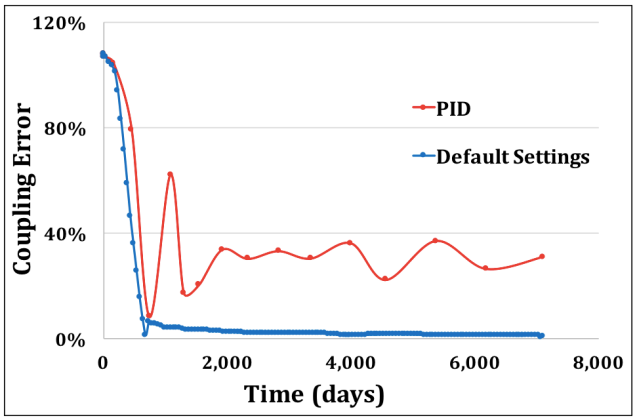

Fig. 12. Coupling error in scheduled gain PID/default

8. CONCLUSION

Our work shows that a PID controlled adaptive-time stepping scheme is superior to an existing commercial standard with regards to computationally efficiency. We have shown the controller mitigates error to acceptable levels while greatly improving the speed of the simulation. The modified Moller and scheduled gain results suggest that controller gain optimization may further improve upon our methods. Our time savings warrant additional testing in larger, complex reservoirs.

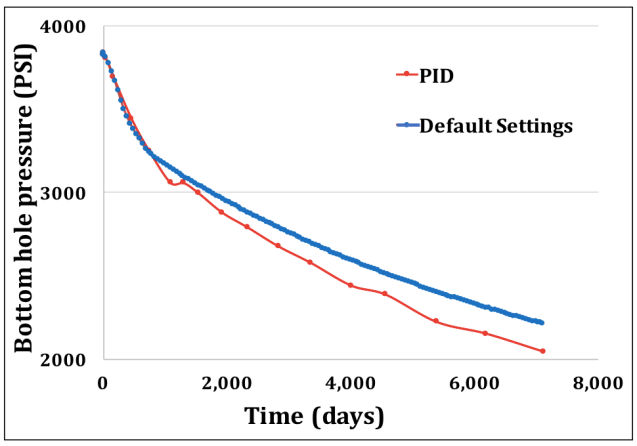

Fig. 13. Bottom hole pressure in scheduled gain PID/default

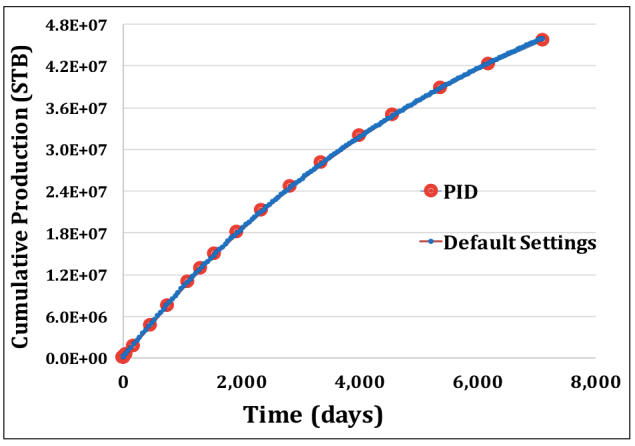

Fig. 14. Cumulative production in scheduled gain PID/default

9. REFERENCES

Akakpo, D., and Gildin, E. (2017). A control perspective to adaptive time-ttepping in reservoir simulation. In: SPE, SPE Reservoir Simulation Conference. Montgomery, Texas, USA, 20-22 February 2016. SPE.

Byer, T. J., Edwards, M. G., and Aziz, K. (1998). Preconditioned newton methods for fully coupled reservoir and surface facility models. In: SPE, SPE Annual Technical Conference and Exhibition. New Orleans, LA, USA, 27-30 September, 1998. SPE.

Cao, H., Samier, P., Kalunga, H.M., Detige, E., and Obi, E. (2015). A fully coupled network model, practical issues and comprehensive comparison with other integrated models on field cases. In SPE: SPE Reservoir Simulation Symposium. Houston, TX, USA, 23-25 February 2015. SPE.

Coats, B. K., Fleming, G. C., Watts, J. W., Rame, M., and Shiralkar, G. S. (2014). A generalized wellbore and surface facility model, fully coupled to a reservoir simulator. SPE Reservoir Evaluation and Engineering, 7, 132-42.

Dempsey, J. R., Patterson, J. K., Coats, K. H., and Brill, J. P. (1971). An efficient model for evaluating gas field gathering system design. Journal of Petroleum Technology, 23, 1067-72.

Emanuel, A. S., and Ranney, J. C. (1981). Studies of offshore reservoir with an interfaced reservoir/piping network simulator. Journal of Petroleum Technology, 33, 399-405.

Gustafsson, K., Lundh, G., and Soderlind, G. (1988). A PI stepsize control for the numerical solution of ordinary differential equations. BIT Numerical Mathematics, 28, 270-87.

Guyaguler, B., Zapata, V. J., Cao, H., Stamati, H. F., and Holmes, J. A. (2011). Near-well-subdomain simulations for accurate inflow-performance-relationship calculation to improve stability of reservoir/network coupling. SPE Reservoir Evaluation & Engineering, 14, 634-644.

Hairer, E., and Wanner. G. (1996). Solving ordinary differential equations II. Second revised edition with 137 figures. Verlag: Springer.

Hepguler, G., Santanu B., and Bard W. (1997). Integration of a field surface and production network with a reservoir simulator. SPE Computer Applications, 9, 88-92.

Jensen, O. (1980). An automatic time-step selection scheme for reservoir simulation. In: SPE, SPE Annual Technical Conference and Exhibition. Dallas, Texas, USA 21-24 September 1980. SPE.

Mengdi, G., (2014). Reservoir and surface facilities coupled through partially and fully implicit approaches. MS. Texas A&M University.

Peaceman, D. W. (1978). Interpretation of well-block pressures in numerical reservoir simulation. Society of Petroleum Engineers Journal, 18, 183-94.

Startzman, R. A., Brummett W. M., Ranney, J. C., Emanuel, A. S., and Toronyi, R. M. (1977). Computer combines offshore facilities and reservoir forecasts. Petroleum Engineer International, 49, 65-74.

Soderlind, G., and Wang, L. (2006). Adaptive time-stepping and computational stability. Journal of Computational and Applied Mathematics, 2, 225-243.

Valli, A. M. P., G. F. Carey, and Coutinho, A. L. (2002). Control strategies for time-step selection in simulation of coupled viscous flow and heat transfer. Communications in Numerical Methods in Engineering, 18, 131-139.

Zhang, Y., Gaurav S., and Jianping, C., (2017). A novel IPR calculation technique to reduce oscillations in time-lagged network-reservoir coupled modeling using analytical scaling and fast marching method. In: SPE, SPE Reservoir Simulation Conference. Montgomery, Texas, USA, 20-22 February. SPE.