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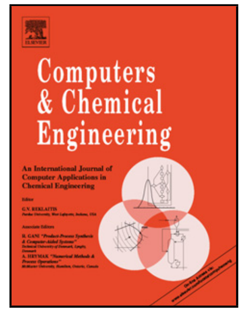

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Authors: Farzad Hourfar, Behzad Moshiri, Karim Salahshoor, Ali Elkamel

PII: S0098-1354(17)30264-8
DOI: http://dx.doi.org/doi:10.1016/j.compchemeng.2017.06.018
Reference: CACE 5849

To appear in: *Computers and Chemical Engineering*

Received date: 14-4-2017
Revised date: 13-6-2017
Accepted date: 14-6-2017

Please cite this article as: Hourfar, Farzad., Moshiri, Behzad., Salahshoor, Karim., & Elkamel, Ali., Real-time Management of the Waterflooding Process Using Proxy Reservoir Modeling and Data Fusion Theory.*Computers and Chemical Engineering* http://dx.doi.org/10.1016/j.compchemeng.2017.06.018

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Real-time Management of the Waterflooding Process Using Proxy Reservoir Modeling and Data Fusion Theory

Farzad Hourfar[a,1*,2], Behzad Moshiri[a], Karim Salahshoor[b], Ali Elkamel[c,1*]

[a] Control & Intelligent Processing Center of Excellence (CIPCE), School of Electrical & Computer Engineering, University of Tehran, Tehran, Iran

[b] Department of Automation & Instrumentation Engineering, Petroleum University of Technology, Ahwaz, Iran

[c] Department of Chemical Engineering, University of Waterloo, Ontario, Canada

[1*] Corresponding Authors: Farzad Hourfar (f.hourfar@ut.ac.ir), Ali Elkamel (aelkaeml@uwaterloo.ca)

[2] Present Address: Visiting Scholar at Department of Chemical Engineering, University of Waterloo,

Ontario, Canada

Highlights

- An adaptive algorithm is introduced for waterflooding management in oil reservoirs using proxy models.
- Time-varying nature and the inherent nonlinearity of the complex process is successfully handled.
- Variations in market prices or operational costs are compensated such that a desired feasible profit is ensured.
- Using data fusion technique, the real-time profitability/productivity status of the reservoir is monitored.
- Fairly profit-sharing in different field development contracts can be achieved by applying the proposed method.

Abstract

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Waterflooding is the use of water injection to enhance the oil recovery in mature oil reservoirs. In this paper an adaptive algorithm has been introduced for waterflooding management in oil reservoirs based on proxy modeling technique. The presented approach is capable to handle the time-varying nature and the inherent nonlinearity of the complex process. In addition, any variation either in market prices or in operational costs is compensated by the designed adaptive controller to fix the obtained profit (here, the net present value: *npv*) at a desired achievable value. The observed outcomes on 10th SPE-Model#2 benchmark case study have shown that by using this algorithm, any feasible desired trajectory for the expected benefit can be satisfied during the waterflooding-based production. Since the suggested controller has adaptive structure, it can be re-adjusted continuously in each time-step, using available operational data, to take into account the reservoir dynamical variations as well as the external disturbances to present an acceptable performance. By including a monitoring module in the algorithm structure based on data fusion technique, the updated profitability/productivity status of the reservoir is estimated. By using this information the *npv* setpoint induced to the closed-loop system can be automatically re-adjusted such that it always remains in an acceptable and reasonable range. In conclusion, the proposed methodology is an applicable solution for fairly profit-sharing in different kinds of contracts. In other words, the gained profit can be appropriately allocated to the shareholders according to the contractual obligations or a defined *npv* trajectory while considering the current condition of the reservoir. This strategy helps to prevent from ultra-production in a specific period of time by the clients or contractors which may lead to an unexpected reduction in the share of other parties in the reservoir life-cycle.

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Keywords: Waterflooding Process; Adaptive Control; Proxy Reservoir Modeling, Data Fusion, Self-Optimizing-Control; Reservoir Management

1. Introduction

For reducing the gap between demand and sources of hydrocarbon-based energy, an effective solution is increasing the oil recovery factor in existing reservoirs. The average recovery factor may disappointingly come down to about 15% in complex reservoirs (Sarma, 2006; Golder Associates). However; by using secondary production approaches such as waterflooding- in which water is injected into the reservoir for conducting the oil toward production wells for more efficiency- up to 70% of the hydrocarbon can be recovered theoretically (van den Hof et al., 2009). So, different aspects of waterflooding modeling, control and optimization studies, have recently attracted much attention by the researchers (Sarma et al., 2006; Shirangi, and Durlofsky, 2015; Grema, and Cao, 2016; Sorek et al., 2017).

Although hydrocarbon production is a complex large-scale dynamical process, the operators in the fields mostly manage it just based on their own experiences. Fortunately, widespread applications of advanced instrument and control devices have increased the opportunity to optimize the oil production using model-based control and optimization techniques (Jansen et al., 2008). Nowadays, intelligent reservoirs are generally equipped with appropriate sensors and actuators to monitor the wells and reservoir conditions as well as to control the fluids flow of the producing and injecting wells. It has been perceived that applying advanced monitoring and control systems in reservoirs can significantly increase the hydrocarbon recovery (Glandt, 2005).

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Closed-loop reservoir management (CLRM) is a popular methodology, which take into account the reservoir observed data as well as the information obtained from model-based simulations, to design the suitable optimal control strategies (Foss, 2012). Generally, the manipulated variables in a reservoir are bottom-hole pressures (*bhp*) or flow-rates of the wells, and the ultimate goal in CLRM is to maximize an objective function which is usually selected as the net present value (*npv*) of the recovery process subject to the operational constraints. In other words, optimization in oil reservoirs can be performed by adjusting optimum injection and production rate settings for maximizing the *npv* as a well-known profitability index. In model-based optimization approaches which use open-loop configuration, the reservoir models are supposed to be perfect in presenting all existing dynamics of the system (Asadollahi and Naevdal, 2009). Consequently, open-loop techniques, such as dynamic optimization, suffer from loss of robustness against uncertainties and may deduce suboptimal or even non-optimal results (Brouwer and Jansen, 2004). On the other hand, robust optimization techniques, which use a set of reservoir realizations for considering different types of probable geological models, have been introduced to cope with the uncertainties (van Essen et al., 2009). However, these methods' principle assumption, which is all existing reservoir characteristics and production behaviors are presented by the developed realizations, is somehow unrealistic (Grema, and Cao, 2016). That is to say, the set of various realizations may not be completely successful to reflect the real reservoir dynamic which is needed for an efficient optimization process.

From another point of view, in model-based dynamic reservoir optimization using direct methods, it is possible to define the optimal control problem in the framework of nonlinear programming (NLP) (Binder et al., 2001). In this methodology, the optimizer seeks for the solution sequentially. It means that a control profile is computed at each step and then the obtained profile is simulated

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for investigating the results. This sequential-optimization process is generally known as single shooting (SS) (Jansen, 2011). For instance, generalized reduced gradient (Kraaijevanger et al., 2007), and augmented Lagrangian (Chen et al., 2010) are common gradient-based methods for dealing with NLP's, specially applied in reservoir optimization. In these techniques, gradients of the objective and function evaluations should be computed. In addition, existence of operational constraints forces some limitations on *bhp*'s and flow-rates of the wells. Function evaluations is the technical term for presenting the dynamic behavior of the reservoir and can be achieved using valid simulators. Furthermore, objective gradient can be calculated via adjoint techniques. However, existence of nonlinear constraints can dictate additional adjoint simulations and increase the computational load of such techniques. As a result, methods to lump reservoir output constraints, such as limitation on the volume of the produced water, into a single constraint have been developed to evade from extra adjoint computations (Suwartadi et al., 2011; Kourounis et al., 2014). Nevertheless, these approaches may induce extra approximations as well as parameters retuning. To handle the mentioned problem related to the output constraints, direct method for dynamic optimization in oil reservoirs based on multiple shooting (MS) technique, has been proposed in (Codas et al., 2015). But, applying this approach requires an intense interaction between optimizer and simulator, which causes to a huge computational load. In addition, to achieve an efficient MS implementation, parallel-computing facilities and extensive-memory should be available. Moreover, several research on reservoir optimization and production management based on proper orthogonal decomposition (van Doren et al., 2006) and trajectory piecewise linearization (Cardoso and Durlofsky, 2010; Gunnerud and Foss, 2010) have tried to develop methods in which the search-space and also memory requirements decrease.

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Obviously, all model-based approaches applicable for the production management in the hydrocarbon reservoirs require accurate reservoir models. A real reservoir can expose totally different behaviors compared to the assumed models. As a result, by just relying on the outcomes of cumbersome model-based optimization techniques, which have been validated in simulation mode while ignoring the real-time production data, the optimization goals may not be achieved in the real applications. This fact has origin in continuous time-varying dynamics of the reservoir as well as the impacts of unknown geological and financial uncertainties during the operation. In other words, in the presence of uncertainties, implementation of appropriate control strategies for optimizing purposes is completely a challenging task. Hence, although many contributions which apply different control techniques use reservoir models to identify the optimal response (Sarma et al., 2005; Jansen et al., 2009), the obtained results are not applicable in practice since the considered models are rarely predictive.

When a batch of new information such as recent production data, up-to-date well logs, and new seismic data are provided during the operation in the oil fields, the utilized reservoir model(s) may be updated by history matching process. Therefore, new optimization calculations would be done based on the updated reservoir models (Foss and Jensen, 2011). Yet, even history-matched models may not be able to forecast the future behavior of reservoirs precisely (Tavassoli et al., 2004). Consequently, instead of periodically updating of the reservoir models via history matching process, closed-loop control strategies based on last measured production data have been introduced (Foss and Jensen, 2011; Jansen et al., 2008).

In other words, besides utilizing complicated model-based methods for optimization objectives, either gradient-based or derivative-free techniques (Chen et al., 2008; van Essen et al., 2011; Ciaurri et al., 2011; Giuliani and Camponogara, 2015; Wang et al., 2016), exploring for more

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realistic solutions, which profit from simplicity in comparison with fully model-based optimization approaches, is an active research area in this domain (Foss and Jensen, 2011; Shuai et al., 2011; Reynolds and Oliveira, 2013; de Holanda et al., 2015). To this aim, there have been some attempts to consider the CLRM as a regulatory feedback control problem (Grema, and Cao, 2016; Güyagüler et al., 2010; Grebenkin and Davies, 2010). Generally, the characteristic of direct feedback-control robustness against unknown reservoir uncertainties is one of the strengths of this approach (Chen et al., 2012). It means that by applying feedback control strategy, the performance becomes less sensitive to model errors and inherent uncertainties of the oil reservoirs. The obtained results in (Dilib and Jackson, 2013; Dilib et al., 2015) demonstrate that closed-loop control methodology which is based on direct feedback between reservoir monitored variables and production flows can lead to near optimal achievements in oil reservoirs. Closed-loop feedback control of the reservoir can also alleviate the effect of existing geological uncertainties on reservoir behavior.

Based on the above explanations, transforming the complicated reservoir optimization problem to the regulatory control framework is among the possible solutions which can have acceptable efficiency, simplicity, and potential of being easily implemented in practice. On the other hand, due to the nature of an oil reservoir and different uncertainty sources, field noises and disturbances during the operation, self-optimizing-control (SOC) strategy can be a proper candidate for optimizing the waterflooding process under certain conditions (Grema, and Cao, 2016). It has been proved that if the controlled variables are selected appropriately in SOC framework and also regulated such that they remain constant during the operation, the system is near optimal even in the presence of uncertainty and disturbances (Skogestad, 2000, 2004, Halvorsen et al., 2003). As a result, controlled variables (CV's) determination which can be an appropriate combination of

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available measurements is an important step in SOC methodology. Clearly, by fixing the selected CV(s) around a specific set-point through feedback control, the optimality or near-optimality of the whole system can be guaranteed (Girei et al., 2014; Hu et al., 2012; Ye et al., 2013).

Another important issue is that of finding an efficient strategy of water injection in waterflooding process as an efficient oil recovery technique in reservoir management, availability of a valid simulator or a precise mathematical model for estimating the quality of the process performance is a vital prerequisite (Fanchi, 2001). Various simulation and modeling approaches with different levels of complexity exist for presenting the reservoir behavior during the operation. Utilization of each modeling methodology is related to the available information, the level of required accuracy, the calculated time-cost, and the user's expectation from modeling and simulation (Ertekin et al., 2001). For example, the prevalent and precise but complex and memory-demanding solution for reservoir simulation, generally used by professional simulators, is numerically solving of a set of partial-differential equations by discretizing in time and space (Chen et al., 2006). Furthermore, exploring for fast modeling strategies with acceptable accuracy is a hot topic in reservoir modeling studies which results to proxy/surrogate models (Sayyafzadeh et al., 2011). The surrogate models are appropriate tools for estimating the performance of various control and optimization strategies in oil reservoirs. The models can be categorized based on their applications as linear and nonlinear; or fixed and adaptive. Each of the proposed modeling strategies has different advantages which make them suitable for distinct cases of various reservoir types based on the user expectation (van Essen et al., 2012; Tafti et al., 2013; Bruyelle and Guérillot, 2014; Mohaghegh and Abdulla, 2014; Elkamel, 1998).

Due to the time-varying nature of the waterflooding process, applying appropriate adaptive modeling structures for representing the dynamical behavior based on the last observed production

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data is inevitable. For example, in (Hourfar et al., 2016) an adaptive linear-based approach for proxy modeling of waterflooding process in oil reservoirs has been presented. The developed modeling technique is completely compatible for being utilized by popular adaptive control and optimization strategies to enhance the economic performance of the reservoir while the production is feasible.

In this paper, based on the adaptive modeling technique presented in (Hourfar et al., 2016), by which the defined system outputs can be modeled using the recommended system identification (*SI*) algorithm, an adaptive control configuration has been developed for production management via waterflooding process. So needless to directly challenge with the reservoir PDE's to assess the production management algorithm, by utilization of the proxy-model the required information about the appropriate injection/production profiles can be provided not only with low computational cost but also with acceptable accuracy.

In addition, considering SOC concepts allows to transform the challenging and complicated task of reservoir optimization to a popular regulatory control problem by properly defining the controlled variable. In other words, by maintaining the suitable considered controlled variable at a constant value, the system can present near optimal behavior with minimum sensitivity to the existing disturbances under certain circumstances. Another advantage of the developed algorithm is providing the capability of controlling the waterflooding process while coping with the inherent time-varying nature of the oil reservoir and also the hydrocarbon market. Adding the adaptation characteristics to the designed controller enables the procedure to track the reservoir dynamic variations and re-adjust the controller parameters for effectively regulating the specified controlled variable. Furthermore, design of a condition monitoring module for the reservoir, using ordered weighted averaging (OWA) method which is known as one of the popular data fusion techniques,

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helps to modify the set-point of the controller by taking into account the last productivity status of the reservoir. Embedding this unit in the general configuration of the algorithm assists to prevent ultra-expectation of the closed-loop system performance. That means whenever the reservoir is impotent to produce the sufficient hydrocarbon due to the production history and the amount of total extracted hydrocarbon, the condition will be detected and consequently a new rational controller set-point will be substituted. Online monitoring of the reservoir condition also facilitates applying the developed methodology in practical applications especially for different types of field development international or multilateral contracts in which a compromise between short-term and long-term production plans is necessary during the operation. Since the produced hydrocarbon and the gained profit are mostly the challenging concerns between the host governments (known as the clients) and the international oil companies (IOC's) (known as the contractors), precisely controlling and managing the obtained profit by appropriately regulating the production regime in various operational phases are important issues. Hopefully, the presented technique helps to monitor and control the expected *npv* based on reservoir and market conditions. This fact makes the algorithm applicable for different types of contracts such as buyback or production sharing (Ghandi and Lin, 2012, 2014; Feng et al., 2014; Zhao et al., 2012; Shakhsi-Niaei et al., 2014). Based on the highlighted characteristics, it can be easily deduced that the developed methodology is perfectly suitable for being implemented in real-time reservoir closed-loop management during the waterflooding process.

2. Comprehensive Modeling of Oil Reservoir Dynamics

As explained in section 1, availability of a valid model is one the most important prerequisites for design and development of a useful controlling strategy during waterflooding operation.

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Conservation of mass and momentum equations are commonly applied for representing the fluid flow behavior in oil reservoirs and the dynamics of waterflooding process may be simulated based on the reservoir partial differential equations. By ignoring gas phase existence and just focusing on oil and gas, the reservoir simplified model equations can be realized (Jansen et al., 2008; Aziz and Settari; 1979). Mass balance for the two existing phases (i.e. oil and water) in the reservoir can be described as in (1):

$$\nabla(\rho_i u_i) + \frac{\partial}{\partial t}(\phi \rho_i S_i) = 0; \quad i \in \{o, w\}, \tag{1}$$

where t is time, ∇ is the divergence operator, ϕ is the porosity, ρ_i is the density of the phase *i*, u_i is the superficial velocity, S_i is the saturation, defined as the proportion of the pore space occupied by phase *i*, in which *o* and *w* are the used symbols for oil and water, respectively. In addition, conservation of momentum can be concluded by the Navier-Stokes equations. The simplified version can also be obtained by semi-empirical Darcy's equation for-low velocity flow through porous materials as follows (while gravity is ignored):

$$u_i = -k\frac{k_{ri}}{\mu_i}\nabla p_i, \qquad i \in \{o, w\},. \tag{2}$$

in which p_i is the pressure of phase i, k is the absolute permeability, k_{ri} is the relative permeability and μ_i is the viscosity of phase i. The permeability k is an inverse measure of the resistance fluid encounters while flowing in a porous medium. The relative permeability k_{ri} relates to the additional resistance that phase i experiences when other phases exist. Since the relationship between relative permeabilities and water saturation is totally nonlinear, the reservoir model is a nonlinear system. Substituting *(2)* into *(1)* leads to two flow equations with four unknowns, P_o, P_w, S_o and S_w. Hence, two other equations are required for completing the system description.

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The first trivial one is:

$$S_o + S_w = 1, \tag{3}$$

and the second necessary equation, named the capillary pressure equation is:

$$p_{cow} = p_o - p_w = f_{cow}(S_w). \tag{4}$$

By substituting *(3)* and *(4)* into the flow equations while considering the oil pressure p_o and water saturation S_w as primary state variables of the system, the following relations can be obtained:

$$\nabla(\tilde{\lambda}_o \nabla p_o) = \frac{\partial}{\partial t}(\phi \rho_o \cdot [1 - S_w]), \tag{5}$$

$$\nabla(\tilde{\lambda}_w \nabla p_o - \tilde{\lambda}_w \frac{\partial p_{cow}}{\partial S_w} \nabla S_w) = \frac{\partial}{\partial t}(\phi \rho_w S_w), \tag{6}$$

in which $\tilde{\lambda}_o = k\dfrac{k_{ro}}{\mu_o}$ and $\tilde{\lambda}_w = k\dfrac{k_{rw}}{\mu_w}$ are the oil and water mobilities. Flow equations *(5)* and *(6)* are defined over the entire volume of the reservoir. It is also assumed that there is no flow across the boundaries of the reservoir geometry over which *(5)-(6)* are defined (Neumann boundary conditions). After discretizing the above equations in the space, a system consists of finite number of *grid blocks* would be built up. The next step in modeling is discretization the equations in time domain to achieve to the following state space form results:

$$\mathbf{V}(\mathbf{x}_k) \cdot \mathbf{x}_{k+1} = \mathbf{T}(\mathbf{x}_k) \cdot \mathbf{x}_k + \mathbf{q}_k, \qquad \mathbf{x}_0 = \overline{\mathbf{x}}_0, \tag{7}$$

in which *k* is the time index. In addition, $\mathbf{x}$ is the state vector constructed by the oil pressure p_o and water saturation S_w in all grids. $\overline{\mathbf{x}}_0$ is a known vector which includes the values of the initial

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conditions. The impacts of the wells on the dynamics of the reservoir are modeled by a source vector, q_k in equation *(7)*.

$$q_k^j = w^j \cdot (p_{bh,k}^j - p_k^j) \tag{8}$$

where $p_{bh,k}^j$ is the well's bottom hole pressure, j is the index of the grid block containing the well and p_k^j is the grid block pressure in which the well is located. w which is known as the well constant is used for representing the well's geometric factors as well as the rock and fluid properties in the vicinity of the well.

Generally, thousands of grid-blocks and millions of states are needed to describe the dynamics of a real oil reservoir. The professional simulators are mostly developed based on solving the above equations for all grids simultaneously in each time step which leads to a large amount of calculation load for estimating the required states in the reservoir.

It is undeniable that executing further operational analysis on the reservoir such as real-time control or optimization studies, using the explained modeling technique can significantly increase the computational volume. However; utilizing proxy/surrogate modeling techniques will help to evaluate the performance of the waterflooding process as well as to easily design the required controller/optimizer just by considering the simplified models and needless to directly challenge with the complicated PDE's solutions. In addition, since some of the data-driven proxy models have the capacity to be updated regularly based on the recent operational data, they are suitable candidates for being applied in adaptive control framework, utilized in practical reservoir management applications.

3. Data Driven Proxy-Modeling of Oil Reservoir

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A real oil reservoir can be considered as a Multi-Input-Multi-Output system since it may contain 10 to 1000 injection and production wells on which the system inputs and outputs are defined. The candidate models should be able to reflect the nonlinearity as well as the time-varying nature of the reservoir. Generally, *SI* framework applied to a reservoir, the inputs are considered as flow rate or *bhp* of the wells and variables such as oil and water production rates of producing wells are supposed as the outputs. Figure 1 depicts the structure of *SI*-based approach for reservoir modeling, which can be easily utilized by various versions of control theory.

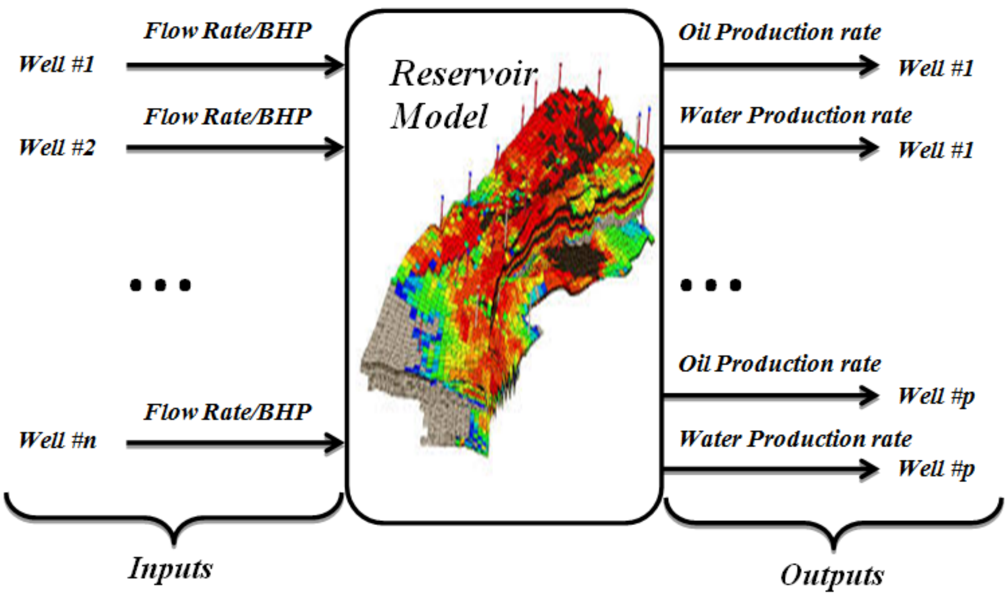

Figure 1. Schematic of oil reservoir model as a controlled system with proper input/output (Hourfar et al., 2016).

In (Hourfar et al., 2016), a proper modeling methodology based on *SI* theory has been proposed for accurately simulating the waterflooding process in oil reservoirs. It has been demonstrated that the presented algorithm is capable of coping with the time-varying nature and nonlinearity of the reservoir in an applicable manner and manage them by linearly modeling of the process dynamics in the vicinity of each operating point as well as updating the proposed model parameters based

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on the available operational data at each sampling time. Since the mentioned modeling technique profits from strong backbone of linear system theories, it can be easily utilized for linear controller or optimizer design and implementation. The appropriate linear mapping between the reservoir inputs, and outputs can be achieved with the following structure:

$$y(k) = A^{-1}(q)B(q)u(k) + v(k) \tag{9}$$

where *u(k)* and *y(k)* are the considered inputs and outputs at time-step #*k*, using the unit delay operator, q^{-1}. In addition, *v(k)* is the representative for the measurement noise or even the model uncertainties and its nature is a zero-mean white Gaussian noise term. Furthermore, matrices *A(q)* and *B(q)* can be presented in the form of matrix fraction description (*MFD*) as:

$$A(q) = \begin{bmatrix} A_{11}(q) & 0 & \cdots & 0 \\ 0 & A_{22}(q) & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & 0 & A_{pp}(q) \end{bmatrix}, B(q) = \begin{bmatrix} B_{11}(q) & \cdots & B_{1m}(q) \\ \vdots & \ddots & \vdots \\ B_{p1}(q) & \cdots & B_{pm}(q) \end{bmatrix}, \tag{10}$$

and so, (9) can be equivalently expressed as (Hourfar et al., 2016):

$$\begin{array}{l} A_{11}{}^{o}(q)y_1(k) = B_{11}{}^{o}(q)u_1(k) + \cdots + B_{1m}{}^{o}(q)u_m(k) + A_{11}{}^{o}(q)v_1(k) \\ \quad\vdots \qquad\qquad\quad \vdots \qquad\qquad\qquad\quad \vdots \\ A_{pp}{}^{o}(q)y_p(k) = B_{p1}{}^{o}(q)u_1(k) + \cdots + B_{pm}{}^{o}(q)u_m(k) + A_{pp}{}^{o}(q)v_p(k) \end{array}, \tag{11}$$

It should be noted that $A_{11}(q)$, ..., $A_{pp}(q)$, introduced in *(10)*, are all monic polynomials. The degrees of $B_{i1}(q)$, ..., $B_{im}(q)$ are equal to or less than that of $A_{ii}(q)$. Using this configuration, *m*-input, *p*-output process is decoupled into *p* *m*-input single output sub-processes. Equation *(11)* implies that each specific output in an oil reservoir such as produced oil or produced water can be expressed based on its previous values and also the inputs. In addition, the parameters of *A(q)* and *B(q)* can be estimated from the input/output data. Due to the time-varying nature of the

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waterflooding process dynamics recursive least square (*RLS*) technique is an acceptable technique for updating the required coefficients. More details on waterflooding data-driven modeling methodology has been provided in (Hourfar et al., 2016).

4. General Formulation of Waterflooding Performance Assessment

The performance of waterflooding process in a certain period of time can be evaluated by calculation of an index which is normally the accumulative *npv*. The accumulative *npv* is defined as the summation of instant *npv*'s of each time step. As mentioned in section 1, in the waterflooding process, water is injected in the reservoir to augment the produced oil or maximize an objective function. In general, the accumulative *npv* is mathematically formulated for a reservoir including N_{prd} production wells and N_{inj} injection wells as (Forouzanfar et al., 2013; Siraj et al., 2016):

$$J = \sum_{k=1}^{K} npv^k = \sum_{k=1}^{K} \left[\sum_{j=1}^{N_{prd}} (r_o . q^k{}_{o,j} - r_w . q^k{}_{w,j}) - \sum_{i=1}^{N_{inj}} (r_{w,inj} . q^k{}_{winj,i}) \right] \frac{\Delta t_k}{(1+b)^{t_k/\tau_t}}, \tag{12}$$

where npv^k is the instant npv at the k^{th} time step. K is the notation for the number of simulation time steps. Δt_k is the length of the k^{th} time step; $q^k{}_{o;j}$ and $q^k{}_{w;j}$ are the averages of oil and water production rates in *STB/Day* or m^3/Day of the j^{th} producer over the k^{th} simulation time step; $q^k{}_{winj;i}$ is the notation for the average injection rate of the i^{th} injection well over the k^{th} simulation time step. In addition, r_o , r_w and $r_{w;inj}$ are the oil price, produced water disposal cost and the water injection cost, respectively, all per unit volume which means in *\$/STB* or $\$/m^3$. Finally, the term b is the discount rate for a certain reference time, τ_t .

Consequently, the vector of well controls, known as manipulated variables in the reservoir which should be specified based on appropriate algorithms for achieving to the higher values of *npv* is:

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$$u = \left[q_{winj,1}^{1}, \cdots, q_{winj,1}^{N_{cs}}, q_{winj,2}^{1}, \cdots, q_{winj,N_{inj}}^{N_{cs}}, q_{o,1}^{1}, \ \cdots, q_{o,1}^{N_{cs}}, \ q_{o,2}^{1}, \ \cdots, \ q_{o,N_{prd}}^{N_{cs}} \right]^{T}, \tag{13}$$

As it is clear, oil production rates as well as water injection rates can be properly adjusted during the operation in N_{cs} distinct control steps.

For the sake of simplicity, by integration of injection wells' flowrates and production wells' flow rates, the accumulative *npv* can be re-expressed as:

$$J = \sum_{k=1}^{K} \left[\frac{r_o.Q_{o,k} - r_w.Q_{w,k} - r_{w,inj}.Q_{inj,k}}{(1+b)^{\frac{t_k}{\tau_t}}}.\Delta t_k \right], \tag{14}$$

in which $Q_{o,k}$, $Q_{w,k}$ and $Q_{inj,k}$ are the notations for the total flow rates of produced oil, produced water and injected water at time step *k,* respectively.

The ultimate goal in waterflooding process is maximizing *J*, by properly adjusting the manipulated variables while taking into account the reservoir internal dynamics and the operational constrains. From operational point of view, the oil and water production rates (assumed as the system outputs) can be determined based on the internal dynamics (considered as the system), and the water injection rates (assumed to be the system inputs). So, without loss of generality, it is justifiable to search for the water injection trajectories, *u's*, which can maximize *J* on specified *bhp*'s of the producing wells:

$$\max_{u} J[u], \tag{15}$$

subjected to:

$$\begin{cases} \dot{x} = f(x,u) \\ y = g(x,u) \end{cases}, \tag{16}$$

and,

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$$\begin{cases} u^{\min} \le u \le u^{\max} \\ \sum u \le U \end{cases}, \tag{17}$$

Equation *(16)* describes the reservoir dynamics and formulate the impacts of the system inputs (*e.g.*: water injection flowrates and producer wells' *bhp*'s) on the reservoir states and outputs. This information can be obtained by using the valid simulators which are generally developed based on PDE models. Furthermore, *(17)* is the generic representation of the operational constraints such as minimum and maximum amounts of injection rates, the existing bounds for the accumulative water injection during the life-cycle or even total injection rate at each time step.

As stated in section 3, *RLS*-based models for the desired reservoir outputs, y_i, can be easily developed. On the other hand, any linear combination of the modeled outputs, entitled as augmented output, *Y(k)*, can also be modeled using the same technique. *Y(k)* can be expressed as:

$$Y(k) = \alpha_1 y_1(k) + \alpha_2 y_2(k) + \cdots \alpha_n y_n(k). \tag{18}$$

It other words, at each time step a linear mapping with appropriate and updated coefficients may be found which is able to present the relationship between the system input(s) and the new defined augmented output. Moreover, since according to *(13)* and *(14)*, the instant *npv* value is a linear combination of produced oil and water- which are defined as reservoir outputs- and the injected water, it is possible to directly model its dynamics using reservoir inputs-outputs data by applying the explained adaptive modeling technique. Clearly, availability of such a model which establish a relation between the injection rates as the manipulated variables and the instant *npv* as the defined output, provides the facility to apply useful adaptive control approaches for real-time management of the reservoir during the operation.

5. Controlling of the Gained Profit:

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Although the instant *npv* is a function of several variables, in this section we demonstrate that under certain conditions, it is possible to fix the *npv* value at a feasible setpoint, just by controlling the total injection rate.

By ignoring the time-varying dynamics of the reservoir and also linearizing the waterflooding process around a specific setpoint, $G_p(s)$ which is the reservoir transfer function from total injected water, U, to the total produced oil, Y_o, can be expressed as:

$$Y_o(s) = G_p(s)U(s). \tag{19}$$

In addition, the instant *npv* can be introduced as the output of the augmented system as follows:

$$npv(s) = r_o Y_o(s) - r_w Y_w(s) - r_{w,i} U(s). \tag{20}$$

where, Y_w is the notation for the total produced water.

A voidage replacement assumption is supposed to be valid. This hypothesis implies that the total water injection and the total production are equal during the operation due to the mass conservation:

$$Y_o(s) + Y_w(s) = U(s). \tag{21}$$

So by combining *(20)* and *(21)*, the instant *npv* can be rewritten as:

$$npv(s) = (r_o + r_w)Y_o(s) - (r_{w,i} + r_w)U(s). \tag{22}$$

or equivalently:

$$npv(s) = \alpha Y_o(s) - \beta U(s). \tag{23}$$

in which, α and β are equal to r_o+r_w and $r_{w,i}+r_w$, respectively. So, considering *(19)* and *(23)* results in:

$$npv(s) = \alpha G_p(s)U(s) - \beta U(s). \tag{24}$$

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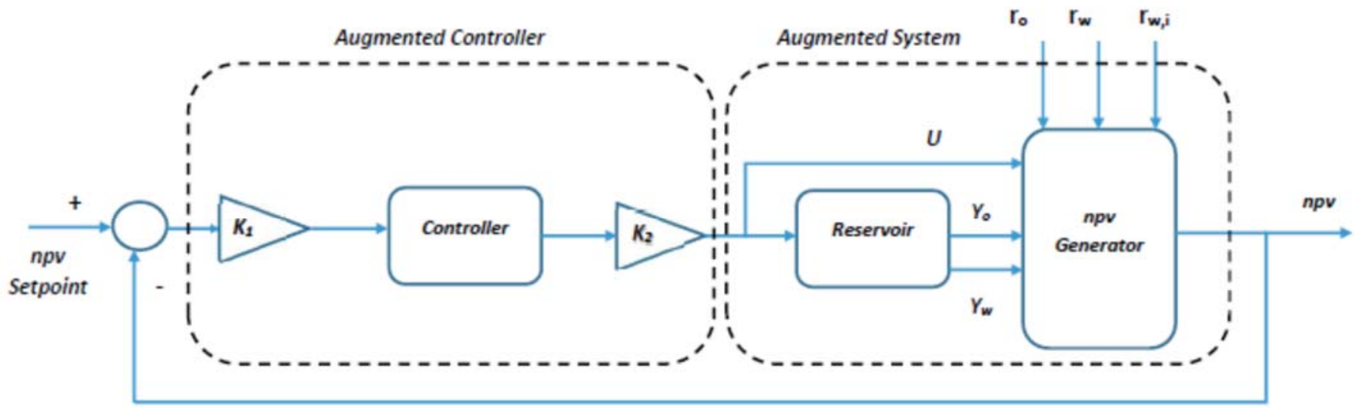

Figure 2. Schematic of the basic closed-loop system for *npv* control.

The basic closed-loop configuration for *npv* control which includes the controller, $G_c(s)$, is represented in Figure 2. K_1 and K_2 are the scaling gains which help to adjust the controller's input/output units and also increase the convergence rate to the desired setpoint. So, the output of the augmented controller, U, is:

$$U(s) = G_c^{aug}(s)(ref - npv), \tag{25}$$

where,

$$G_c^{aug}(s) = K_1 G_c(s) K_2 . \tag{26}$$

By substituting *U(s)* from *(25)* in *(24)*, we will have:

$$npv(s) = (\alpha G_p(s) - \beta) G_c^{aug}(s)(ref - npv). \tag{27}$$

which results in:

$$npv(s) = \frac{(\alpha G_p(s) - \beta) G_c^{aug}(s)}{1 + (\alpha G_p(s) - \beta) G_c^{aug}(s)} ref(s). \tag{28}$$

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On the other hand, well-known Final Value Theorem implies that:

$$\lim_{t\to\infty} npv(t) = \lim_{s\to 0} s \times npv(s) . \tag{29}$$

So, for fixing the *npv* at a desired value, *R*, then reference signal will be:

$$ref(s) = \frac{R}{s} . \tag{30}$$

As a result:

$$\lim_{s\to 0} s \times npv(s) = \lim_{s\to 0} \frac{(\alpha G_p(s) - \beta) G_c^{aug}(s)}{1 + (\alpha G_p(s) - \beta) G_c^{aug}(s)} R , \tag{31}$$

It can be deduced that the above limit converges to *R*, if:

$$\lim_{s\to 0} G_c(s) \to \infty . \tag{32}$$

In other words, by manipulating the total water injection in an oil reservoir and also validity of the voidage replacement assumption the value of *npv* converges to any feasible desired reference value if: *"the controller $G_c(s)$ stabilizes the closed-loop system as well as contains at least a pure integrator."*

In the next section, by using SOC concepts we will demonstrate that under certain circumstances, regulating the amount of the *npv* at a specified value can provide the optimal solution.

5.1. Optimality Condition

The main goal in self-optimizing-control methodology is converting the complicated optimization problem to a straightforward regulatory control problem. To this aim, an appropriate control

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variable (CV) is defined such that by fixing it at a desired set-point, the objective function converges to near optimal or even optimal value.

In general framework of self-optimizing control (SOC), by considering y as the set of available measurements, which can include the waterflooding process inputs and outputs, that represents the system dynamics, the variable c which is going to be regulated is defined as the combination of measured variable, $c = h(y)$. It means that c can be assumed as the combination of injected water and produced oil and water. In addition, although the function $h(y)$ is free to choose, it can be supposed that it is in the form of $H,$ for reflecting the local behavior and remaining in the linear space for combining the different measurement. This assumption implies that:

$$\Delta c = Hy, \tag{33}$$

in which the constant matrix H is free to choose.

Alstad and Skogestad (2002) have demonstrated that it is always possible to find c such that its regulation at a desired set-point leads to optimal solution in the presence of disturbances if no implementation error exists and also sufficient measurements are available. The optimal values of y are functions of disturbances, d, and can be expressed as $y_{\text{opt}}(d)$. So, by linearizing for "small" disturbance variations the following relationship trivial:

$$\Delta y_{\text{opt}}(d) = F\Delta d \,, \tag{34}$$

where F is the constant sensitivity matrix and can be obtained as:

$$F = \Delta y_{opt}(d)/\,\Delta d \,. \tag{35}$$

Since, the main goal in SOC is finding the proper variable combination, it can be written:

$$\Delta c = H\Delta y \tag{36}$$

in which after regulating c at the optimal condition: $\Delta c_{\text{opt}} = 0$.

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As a result:

$$\Delta c_{\mathrm{opt}} = H\Delta y_{\mathrm{opt}} = HF\Delta d = 0\ . \tag{37}$$

Since the above condition should be satisfied for all Δd, H is selected such that:

$$HF = 0\ . \tag{38}$$

In other words, H must be in the left null space of F. More details are available in (Skogestad, 2004; Alstad and Skogestad, 2002).

Based on the above explanations, by selecting $c=h(y)$ as the *npv,* which is the linear combination of the available measurements according to *(14)* including produced oil and water and the injected water, fixing the value of c at a specific value will conclude in an optimal result for all the existing disturbances which satisfies $HF=0$.

In addition, it can be easily inferred that if fixing the *npv* value at a specific set-point leads to an optimal result, scaling the value of the setpoint will also result in the optimal solution. The reason is if *(38)* is satisfied, then:

$$\alpha HF=0\ . \tag{39}$$

or equivalently a new H can be found such that satisfies the following condition:

$$H'F=0 \tag{40}$$

The interpretation of *(40)* in reservoir management is that: fixing the defined c, here the *npv,* at another value and also satisfaction of the mentioned conditions regarding the existing disturbances, will conduct to the optimal result. However; increasing or decreasing the setpoint value for *npv* in a reservoir affects the required time for obtaining the optimal solution. In other words, by adjustment of the *npv* setpoint, it will be possible to achieve to the maximum accumulative profit

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in different times. We will show that this fact is very helpful for profit sharing for revenue sharing in various types of filed development contracts.

6. Relaxing the Limiting Assumptions

In the previous section we exposed that fixing the value of *npv* at a desired value is possible just by manipulating the total injection rate. In addition, this action may lead to even optimal solution under certain conditions. However; since the dynamics of a real reservoir and consequently the waterflooding process is completely nonlinear and time-varying and also the values of oil prices and production costs are not constant during the life-cycle of the reservoir, replacing the fix-structured conventional feedback controller with suitable adaptive controller framework, is inevitable.

To this aim, based on adaptive modeling technique explained in section 3, which is able to handle the nonlinearity and the time-varying nature of the process, we design an appropriate and uncomplicated indirect adaptive controller for managing the production using the information obtained from monitoring of the productivity status of the reservoir. Since simplicity of any proposed technique is an undeniable advantage in practical implementations and applications according to "Parsimony Principle" (Vlahavas and Vrakas, 2008), the introduced controller has been established on a simple but practical adaptive control solution. Needless to clarify that more complex adaptive controller alternatives can also be applied in practice if the uncomplicated strategies are unsuccessful to lead to acceptable results. Another unrealistic assumption is that the reservoir is capable to maintain any desired *npv*. However; according to the production regime and history, the productivity as well as the profitability of the reservoir may vary and so achieving to

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any desired *npv* is thoroughly infeasible in practice. In the following subsections, we explain the solutions for coping with described impractical assumptions.

6.1. Handling the Time-Varying Nature of Waterflooding Process

Based on the specified appropriate adaptive modeling technique, which provides the updated model for the reservoir at each time step, the suitable adaptive controller can be designed for the process.

As mentioned above, according to the "Parsimony Principle" in controller design, an adaptive control scheme, based on self-tuning regulator (*STR*), has been applied to confront with the nonlinear and time-varying characteristics of waterflooding process. The indirect *STR* configuration, leads to controller design with time-varying parameters based on the last updated model of the system. In other words, the controller parameters are adjusted on-line in accordance with the real-time estimation of the waterflooding dynamics. Consequently, the variations in the reservoir dynamics as well as any operational cost/price change can be tracked and compensated by the embedded controller to set the *npv* value at the desired setpoint. It should be clarified that the main reason for utilizing indirect *STR* as an adaptive control approach, is presenting the capability of this well-known but easily implementable controller to cope with the existing challenges in waterflooding process and also demonstrating that there is no need to find a more complicated solution for this problem.

In general, by utilizing the modeling methodology proposed in section 3, any desired output related to the waterlooding process (such as *npv)* can be presented by a discrete time auto-regressive with external input *(ARX*) model as:

$$A(q)y(k) = B(q)(u(k) + v(t)) \tag{41}$$

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Since pole-placement design is a common and popular feedback control technique which can be easily applied in adaptive control framework, just a brief description is given below. More details can be found in (Astrom and Wittenmark, 1995; Zhao et al., 2003; Yang and Gao, 2000).

In adaptive pole placement approach, appropriate for self-tuning regulator design, the control-law is as follows:

$$R(q)u(k) = T(q)r(k) - S(q)y(k) \tag{42}$$

where *r(k)* is the reference signal, *u(k)* and *y(k)* are the controller and system outputs, and *R(q)*, *S(q)*, and *T(q)* are controller polynomials which can be specified during the design problem by applying suitable algorithms such as minimum-degree pole placement (MDPP). In addition, a desired or reference model should be determined by which the closed loop system represents the dynamical behavior similar to the reference model during the operation. This facts implies that the desired output of the system $y_m(k)$, should follow the output of a reference model selected by the designer:

$$y_m(k) = \frac{B_m(q)}{A_m(q)} r(k). \tag{43}$$

Considering *(41*) and *(42*), the closed-loop system can be expressed as:

$$y(k) = \frac{BT}{AR+BS} r(k) + \frac{BR}{AR+BS} v(k), \tag{44}$$

and,

$$u(k) = \frac{AT}{AR+BS} r(k) + \frac{BS}{AR+BS} v(k), \tag{45}$$

So, the closed-loop characteristic polynomial is:

$$AR + BS = A_c \tag{46}$$

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The design problem is to find *R*, *S* and *T* according to following relations:

$$\frac{BT}{AR+BS}=\frac{BT}{A_c}=\frac{B_m}{A_m}, \tag{47}$$

In addition, for minimum degree pole placement (*MDPP*) control, the following conditions should be satisfied:

$$\begin{aligned} &\deg A_m = \deg A \\ &\deg B_m = \deg B \\ &\deg A_o = \deg A - \deg B^+ - 1 \end{aligned} \tag{48}$$

Supposing that:

$$\deg S = \deg A - 1, \tag{49}$$

by solving the well-known *Diophantine* equation, *R'* and *S* can be obtained from *(50)*:

$$AR' + B^- S = A_o A_m, \tag{50}$$

in which, A_o and A_m should be determined by the designer and A_o is the desired observer characteristic polynomials that its maximum degree is similar to deg S. In addition, B^- includes unstable or poorly damped roots and B^+ is the monic stable polynomial with well-damped roots of *B* as follows:

$$B = B^+ B^-, \tag{51}$$

and,

$$B_m = B^- B'_m \ . \tag{52}$$

So, *T* and *R* can be calculated as:

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$$T = A_o B'_m \ . \tag{53}$$

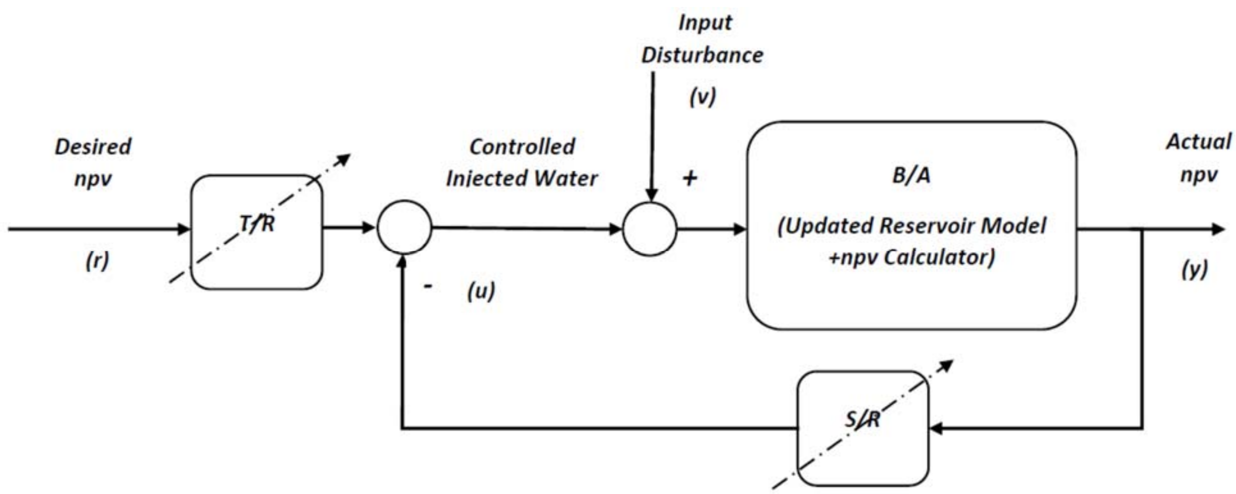
and,

$$R = R' B^+ \ . \tag{54}$$

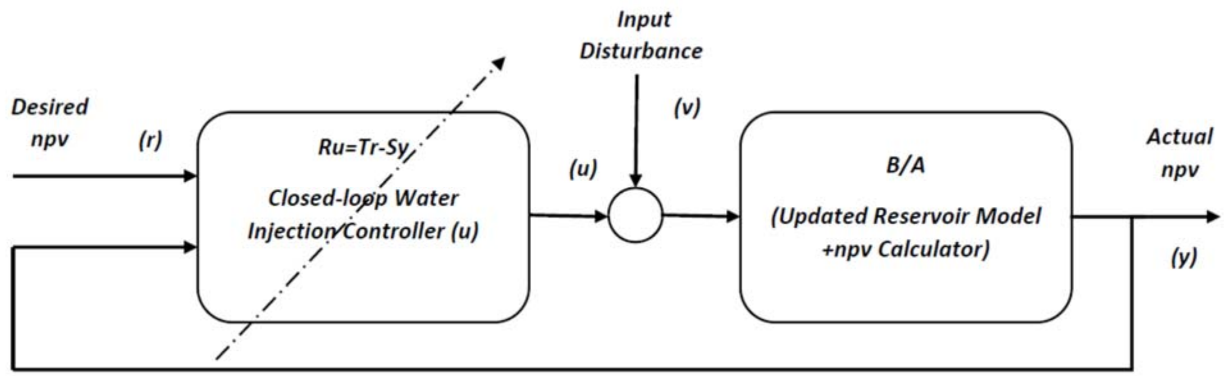
As a result, in the defined adaptive control problem, the relationship between the total injected water, u, the instant npv, y, and the desired npv, r, is:

$$Ru = Tr - Sy \ . \tag{55}$$

Figure 3 illustrates the distributed and lumped configurations for the closed-loop system based on adaptive *STR* controller scheme, applicable in oil reservoirs.



(a)



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(b)

Figure 3. Closed-Loop Structure of Adaptive *STR* Controller for *npv* Management in Oil Reservoirs. a) Distributed Structure b) Lumped Structure.

6.2. Setpoint Adjustment Based on Reservoir Productivity Monitoring

Maintaining the *npv* value constant is not always possible in real application. In other words, due to the dynamic variations as well as the remained oil in the reservoir, the higher *npv* values are not always achievable in the whole life-cycle. This fact causes that re-adjustment of the desired *npv* setpoint during the production becomes unavoidable. To this aim, an appropriate condition monitoring system has been suggested in this paper by which the profitability/productivity status of the reservoir can be inferred. The main task of this module is modifying the desired profit (*npv*) setpoint whenever the injection and production profiles are not able to produce the expected profit. So, by monitoring the available reservoir information, such as watercut of producing wells, and taking into account these data, the reservoir condition monitoring module has been developed. Since data fusion (*DF*) theory has been applied for making valid decision about the hydrocarbon productivity condition of the reservoir, in the next subsection a concise explanation of the *DF* main idea is proposed.

6.2.1. Data Fusion Methodology

By using data fusion theory, a better perception from a specific phenomenon can be achieved by synergistically combining available information from different sources (Waltz and Llinas, 1990). Applying this technique can enhance the resolution and confidence of the final inference compared to individual inferences from various information sources (Khaleghi et al., 2013). In other words,

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in data fusion methodology the data generated by multiple sensors are combined such that an acceptable estimate of the measured quantity is provided. For instance, Bayesian data fusion approach is based on the Bayes Theory with strong theoretical foundation. This technique deals with "probabilities" of events occurrence. Another alternative to efficiently fuse the available data is applying Dempster-Shafer theory which deals with measures of "belief" instead of directly handling of probability. In general, the Bayes and Dempster-Shafer approaches are both based on the concept of assigning appropriate weights to the measured values. In Bayesian data fusion, a "classical" interpretation of probability is applied to calculate the suitable weights. However, in Dempster-Shafer technique by generating a new state corresponding to "unknown" status, the proper weights dedicated to available sensors' outputs are specified (Koks and Challa, 2005; Mitchell, 2007; Liggins et al., 2009). Another practical method to fuse the provided data by the installed sources is based on fuzzy logic and operators. In the following section a popular fuzzy-based technique, which has been utilized in this research to compute the required weights for combining the received information from the appropriate sensors, is explained.

6.2.1.1. Ordered Weighted Averaging (OWA) Operator

OWA operator has been introduced in (Yager, 1988). The OWA operator of dimension n is a mapping $OWA: R^n \rightarrow R$, which has an associated n vector $w=(w_1, w_2,\dots w_n)^T$. w_i are weights with the following properties:

- $w_i \in [0,1]$ ، $1 \leq i \leq n$,

  and,

- $\sum_{i=1}^{n} w_i = w_1 + \cdots + w_n = 1$.

The OWA operator is defined as:

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$$OWA(a_1, \dots, a_n) = \sum_{j=1}^{n} w_j b_j = w_1 b_1 + \cdots + w_n b_n. \tag{56}$$

where b_j is the j^{th} largest element of the collection of the aggregated objects $a_1, a_2, \dots a_n$. The value of $OWA(a_1, \dots, a_n)$, specifies the aggregated value of arguments.

The re-ordering step is the main part for using the OWA operator. OWA operators satisfy properties such as monotonicity, commutativity, and idempotency and their outputs are bounded by the Max and Min operators (Brown, 2004). The "*orness*" has been introduced in (Yager, 1988) to determine the type of aggregation, utilized for a particular value of the weighting vector. The *Orness* is a scale for measuring the degree of similarity between the aggregation and an "*or"* operation and is defined as follows:

$$Orness(w) = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) w_i. \tag{57}$$

For computing the weights in the OWA operators, an exponential class of OWA has been developed (Filev and Yager, 1998) which is able to satisfy a given degree of *orness*. The weights in optimistic exponential OWA operator can be determined by:

$$w_1 = \alpha;\ w_2 = \alpha(1-\alpha); \dots; w_{n-1} = \alpha(1-\alpha)^{n-2}; w_n = (1-\alpha)^{n-1}; \quad 0 \le \alpha \le 1 \tag{58}$$

in which α is related to the *orness* value regarding the number of measurement, *n*. More details on exponential OWA algorithm and also calculating the required weights are available in (Filev and Yager, 1998; Afshar-Khamseh et al., 2016).

7. Developed Algorithm for Production Management

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In this section, the developed methodology for production management in hydrocarbon reservoirs via adaptive control of *npv* based on the productivity/profitability condition of the considered system is summarized. The proposed algorithm is divided into three steps as explained below:

7.1. Initialization

In this phase, all the required information which are utilized in the next phases of the algorithm should be specified. The reservoir geological characteristics, the operational constraints, the hydrocarbon price and also the production costs are some of the necessary data. In addition, the desired expected profit (*npv*) in various time steps (e.g. in each 12 months) is another important issue which should be determined. The *npv* profile can be dictated by the decision makers in the management level or can be determined according to the operational contract terms in which the strategy of profit-sharing between the client and contractors are clarified.

7.2. Adaptive Modeling

Considering the proxy modeling technique explained in section 3, and also taking into account the online production data such as total water injection rate, total produced hydrocarbon and water, and the relevant costs and prices, it will be possible to establish a mapping between the system input (here, total injection rate) and the system output (here, the instant *npv*). According to the proposed structure, the model has the capability to be updated at each time step, based on the new available production data. Consequently, the updated model is constantly used for controller parameters adjustment to achieve the best performance.

7.3. Profit Management and Control

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Based on the desired *npv* profile specified in phase 1 and also the adaptive model obtained in phase 2, the indirect adaptive controller can be implemented using the methodology described in section 6. The controller is able to cope with the time-varying and nonlinear nature of the waterflooding process as well as the deviations in hydrocarbon price and production costs. In other words, this policy helps to maintain the *npv* at the desired value even when the effective production variables change.

On the other hand, although any desired setpoint for the *npv* can be followed theoretically using the indirect adaptive controller approach, the expected profit should be in a feasible and acceptable range. During the production, the controlled variable (here, the *npv*) may start to diverge from the defined setpoint. A probable reason for this event is that the reservoir does not have the ability to produce the required amount of hydrocarbon for retaining the profit. In such a case, the setpoint value should be modified appropriately by considering the current productivity condition of the reservoir for preventing from controller over-expectation which may cause instability in the process by increasing the input continuously and not achieving to the desired setpoint.

Since during the production, instant *npv* drop originates from different factors including the increase in the volume of the produced and injected water in each time step, real-time processing of this information provides the facility to properly adjust the setpoint value for *npv* based on the last productivity status of the reservoir, whenever it is necessary.

To this aim, data fusion theory has been applied in this paper to introduce an index for real-time monitoring of the productivity condition in the reservoir. We entitle this index as the Accumulative Water-Cut Index (*AWCI*). Considering the effect of each producing well on the total produced water, which is one of the major efficacious variables on instant *npv* decrease, the appropriate weights of each producing well water-cut value for calculating the *AWCI* can be calculated using

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optimistic exponential *OWA* methodology, explained in section 6. Decreasing the value of setpoint in percentage, proportional to *AWCI* rise is almost helpful for modifying the setpoint and also detecting the trend of variations in the reservoir dynamics. However, since the amount of produced water is not the only influencing parameter on *npv* drop, it is possible that the control system cannot follow the proposed setpoints with acceptable accuracy. Hence, the effect of water injection which is another major impressive factor in *npv* drop is needed to be taken into account for deducing the proper value of setpoint reduction in percentage. Based on the ratio of the injected and produced water and also considering the relevant costs, the appropriate amount of setpoint variation can be concluded. The flowchart of the explained algorithm has been illustrated in Figure 4. In addition, Figure 5 presents in different modules and interconnects in the developed methodology.

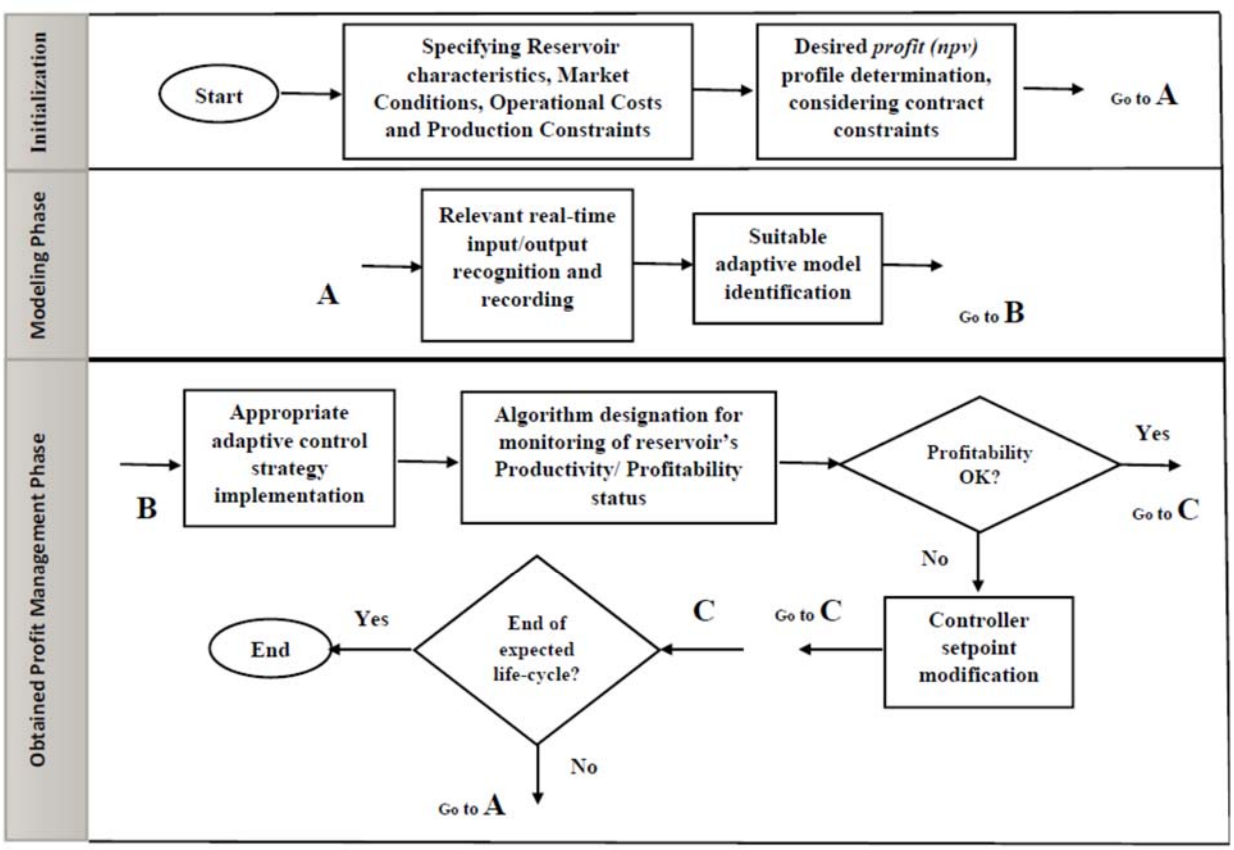

Figure 4. Flowchart of the algorithm.

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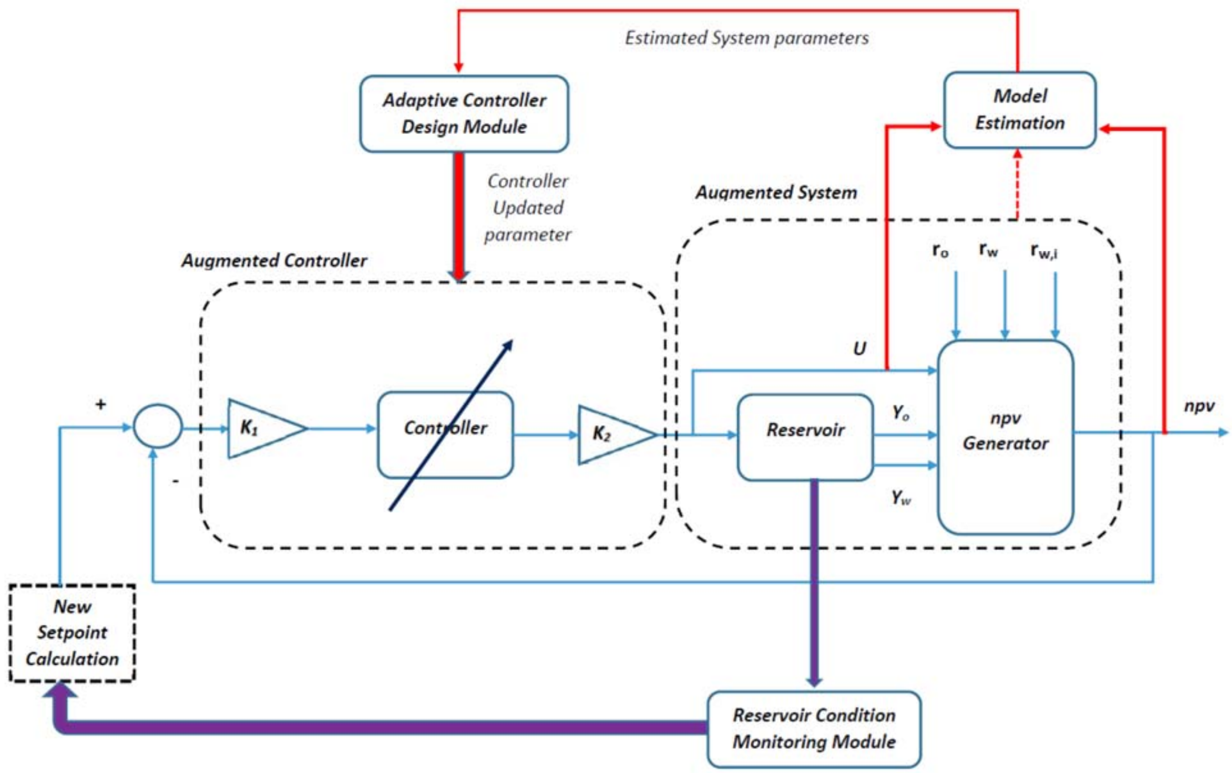

Figure 5. Block-diagram of the modules interconnections in the developed algorithm

8. Algorithm Implementation and Results

The developed waterflooding profit management algorithm has been implemented, using Matlab Reservoir Simulation Toolbox (MRST) environment (Lie, 2014). Without loss of generality, it is assumed that the producing wells are being operated in the fixed *bhp*'s according to operational recommendations. In addition, the annual discount rate in accumulative *npv* formula, is supposed to be zero. Furthermore, the voidage assumption is valid which implies: for over-pressurization prevention, the total injection rate and the total production rate are equal during the production:

$$\sum_{i=1}^{m} q_{i\_inj} = \sum_{j=1}^{p} q_{j\_prod} \,, \tag{59}$$

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where q_{i_inj} is the flowrate of each injection well and q_{j_prod} is the total flowrate of each producing well, while m and p are the number of injection and production wells, respectively.

The developed algorithm is applied to the well-known 10^{th} SPE-Model#2 for reservoir *npv* control via waterflooding process for different practical scenarios which can be imposed by production contract conditions or decision makers in the management level. The geological characteristics of the standard 10^{th} SPE-Model#2 and further information such as well locations (four production wells and one injection well) and initial adjustments are available in (Christie and Blunt, 2001; Islam and Sepehrnoori, 2013).

In all of the studied scenarios it is considered that the sampling time for data is every 10-days. In addition, it is supposed that the useful life-cycle of the reservoir should be at least 3000 days (300 samples), and also one critical point for evaluating the gained profits is at sample #75 (about 2 years from the beginning of the production) according to the assumed contractual obligations. Furthermore, the price of the oil, the water disposal cost and water injection cost are 80$ *bbl/day*, 10$ *bbl/day* and 5$ *bbl/day*, respectively.

The first trivial solution in waterflooding process management can be applying the maximum injection capacity for the oil recovery. However; this policy may cause depletion of the reservoir too much earlier than the expected time. In addition, since the profit sharing is a controversial issue in bilateral or multilateral field development agreements, using this strategy may lead to inequitable outcome sharing between the contractors and the clients, especially in buyback contracts.

Figure 6, Figure 7 and Figure 8 depict the results related to the case in which the total injected water is assumed to be fixed on the maximum value which is 6000 *bbl/day*. Figure 6 demonstrates that the time step #156 is the last step in which the instant *npv* is still positive and after that time,

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the production with the same injection regime is unprofitable. Furthermore, it is clear in Figure 7 that after about 2 years (time step = 75) from the initializing time, 86.7% of the accumulative *npv* has been earned which can be a challenging issue for profit sharing in buyback contracts since most of the reservoir financial gain has been collected by just one of the shareholders. Figure 8 illustrates the total values of different fluids.

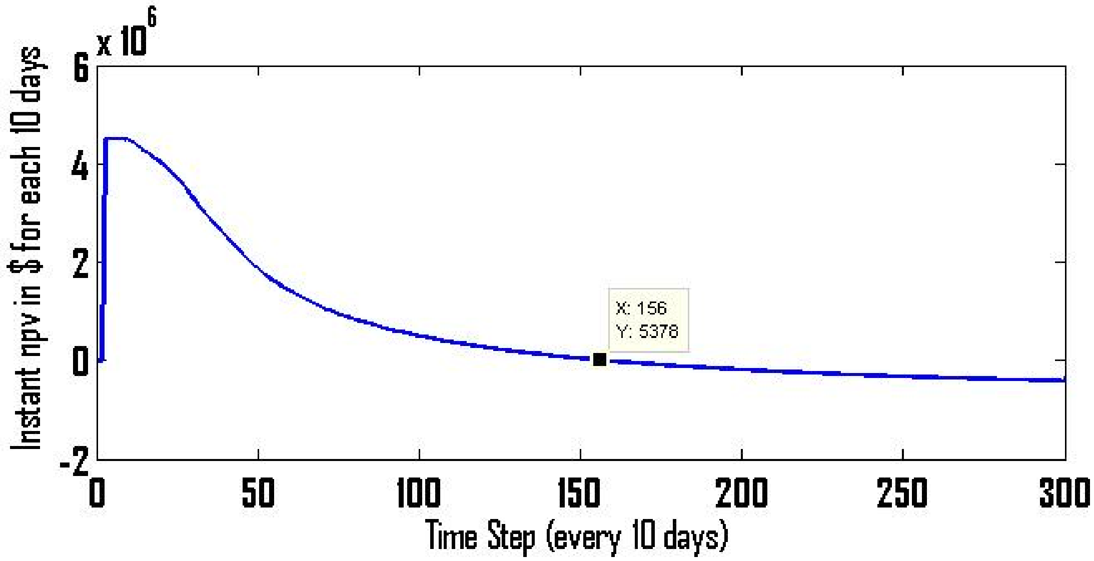

Figure 6. Instant *npv*; total injection rate is fixed at 6000 *bbl/day*

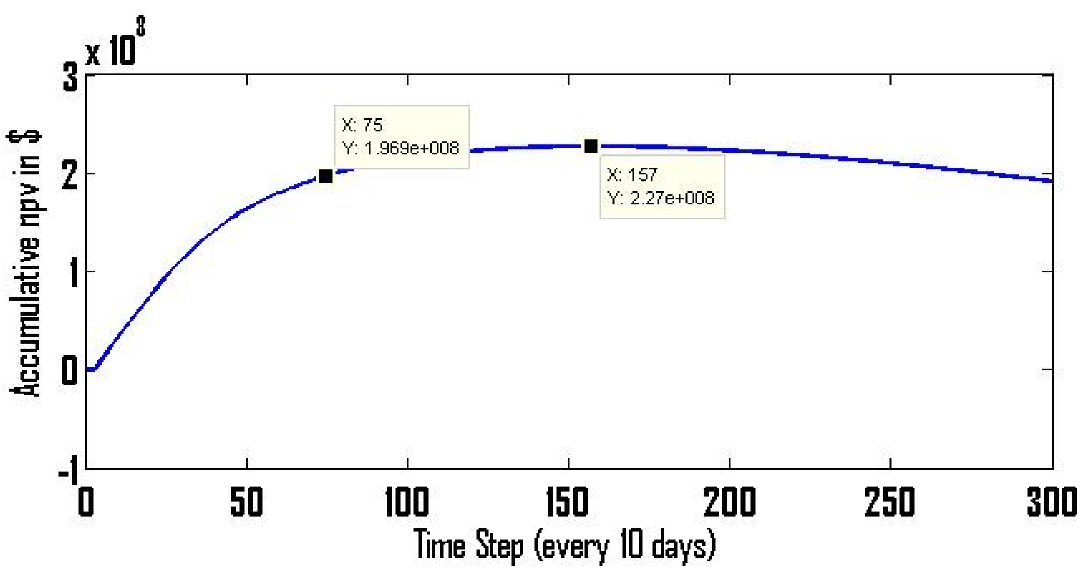

Figure 7. Accumulative *npv*; total injection rate is fixed at 6000 *bbl/day*

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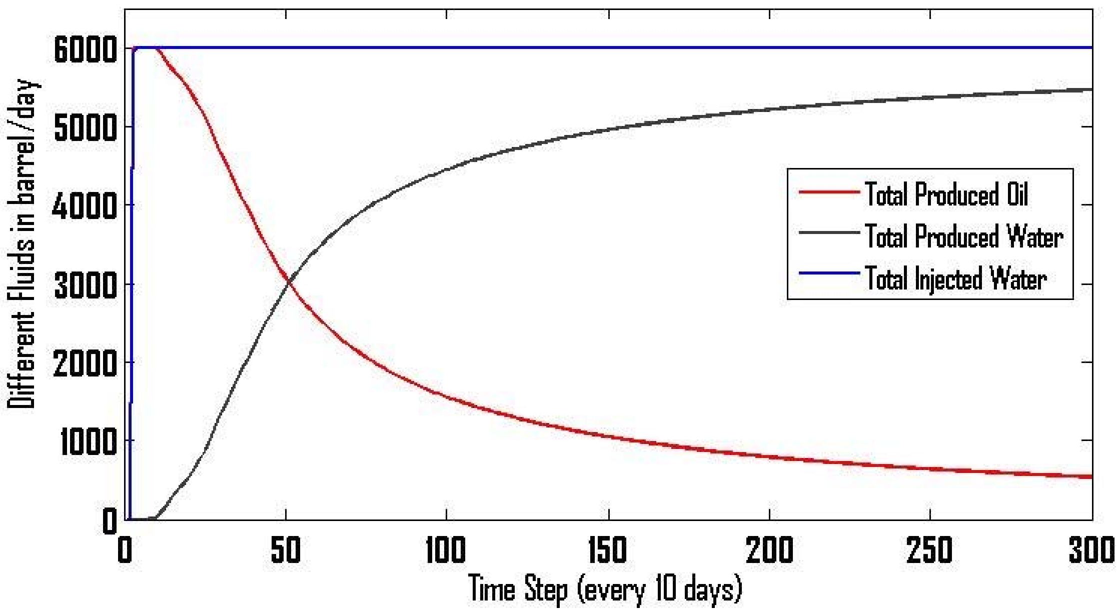

Figure 8. Total oil and water production rates; total injection rate is fixed at 6000 *bbl/day*

Nevertheless, the cost-effective production period can be increased by reducing the value of the total injection rate. For instance, if the total injection rate is fixed on 3000 *bbl/day*, the value of instant *npv* remains positive even up to the time step #311 (Figure 9). In addition, the ratio between accumulative *npv* at the time step #75 and the maximum of accumulative *npv* is decreased to 61% compared to the previous policy (Figure 10). Consequently, it seems that by reducing the maximum injection capacity and applying maximum injection policy the obtained accumulative profit at a specific time and the total profitable production period can be adjusted to some extent. This idea is somehow acceptable since the capacity of the injection facilities can also be diminished which results in initial capital expenditure (capex) reduction. However; the profile of instant *npv* is not precisely controllable yet. In other words, this full injection strategy is still impotent if according to the contractual obligations regarding the production policies, a specific *npv* trajectory

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should be followed up for guaranteeing the fair benefits of all the shareholders at the end of the life-cycle.

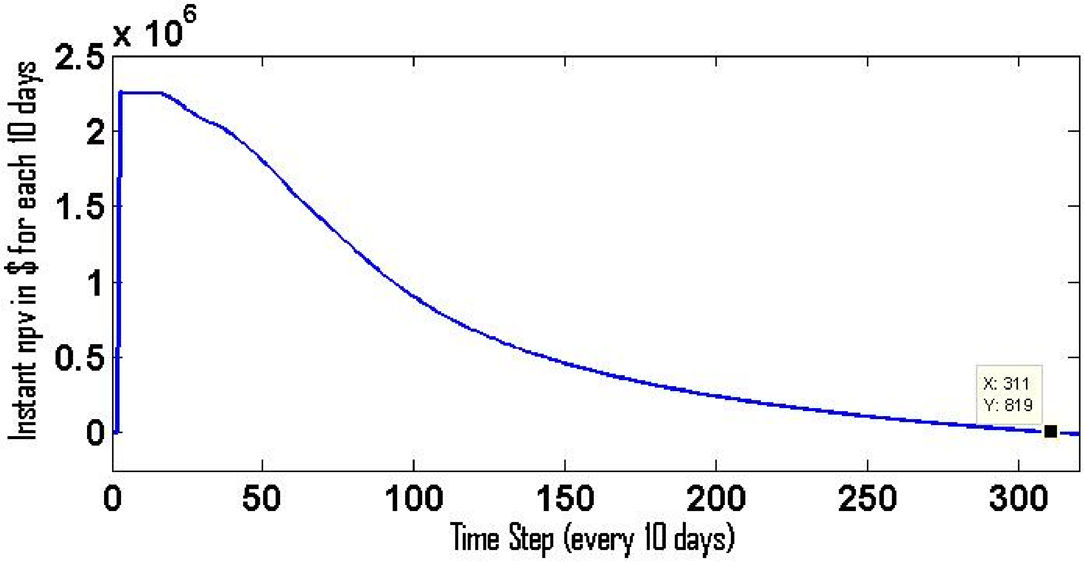

Figure 9. Instant *npv*; total injection rate is fixed at 3000 *bbl/day*

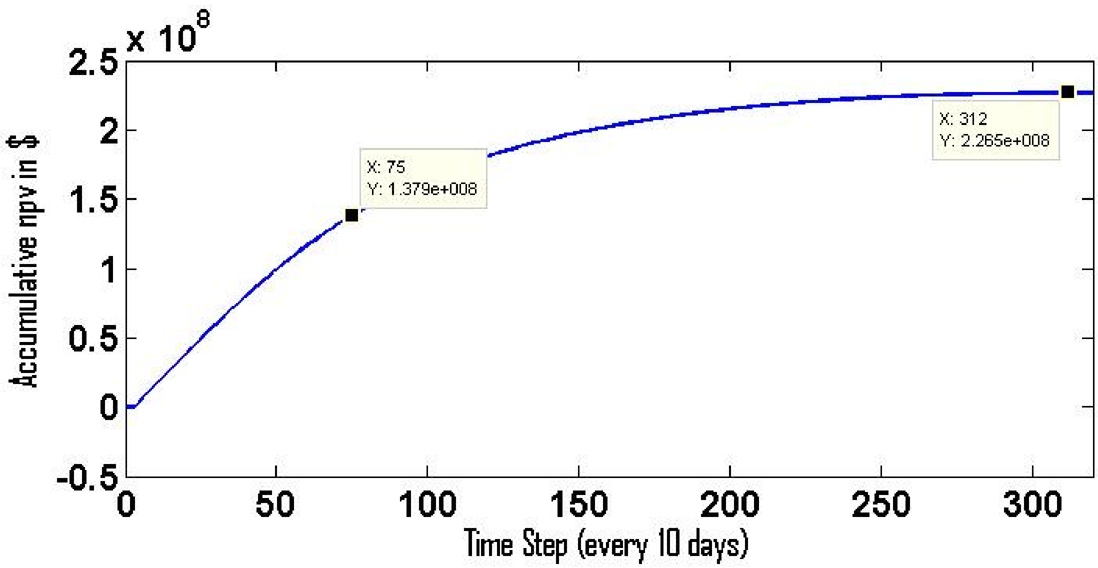

Figure 10. Accumulative *npv*; total injection rate is fixed at 3000 *bbl/day*

Based on several effective factors such as the reservoir's initial conditions and capacity, contractual terms and limitations, and the predicted life-cycle of the operation, a desired set point

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for the instant *npv* value can be proposed for closed-loop profit management. To achieve to this setpoint by manipulating the total injection rate in waterflooding process, an appropriate controller, which is designed on the explanations given in section 6, is applied. It has been also perceived that the value of instant *npv* at sampling time *k, npv(k),* can be appropriately modeled as a function of instant *npv* and total injection rate at time steps *k-1*, *k-2* and *k-3* based on *ARX* structure using Parsimony Principle. Figure 11, Figure 12 and Figure 13 demonstrate the obtained results when the controller is active in the loop. It can be observed that due to the nature of the reservoir and the reduction in the ratio of existing hydrocarbon to the total fluids, the controller gradually becomes incapable to stabilize the value of the instant *npv* at the desired value for the whole production period. It is clear that although the controller starts to raise the manipulated variable (injection rate) even up to the maximum assumed capacity (6000 *bbl/day*) for compensating the drop, the deviation from the assumed setpoint also goes up. In addition, after time step #229 the production with this policy is not at all beneficial. On the other hand, up to the time step #75, just 45% of the total accumulative *npv* has been gained which implies that although we cannot achieve to the perfect control, the profit-sharing issue, which is an important concern in different types of contract, is more manageable in this scenario.

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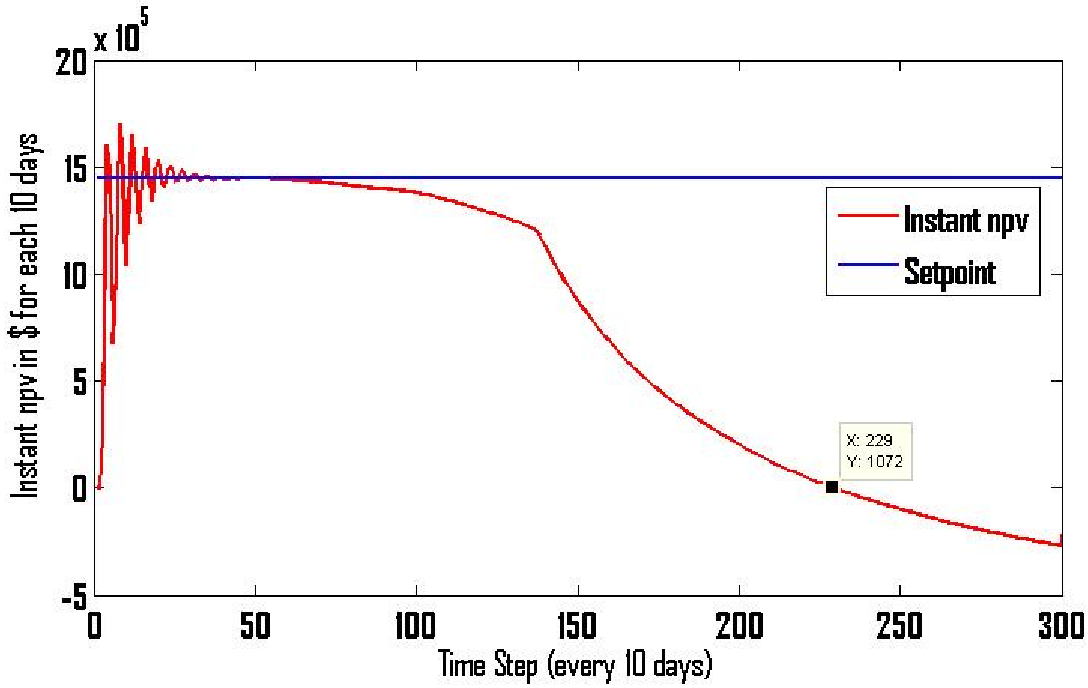

Figure 11. Instant *npv*; controller tries to fix the *npv* at the desired setpoint

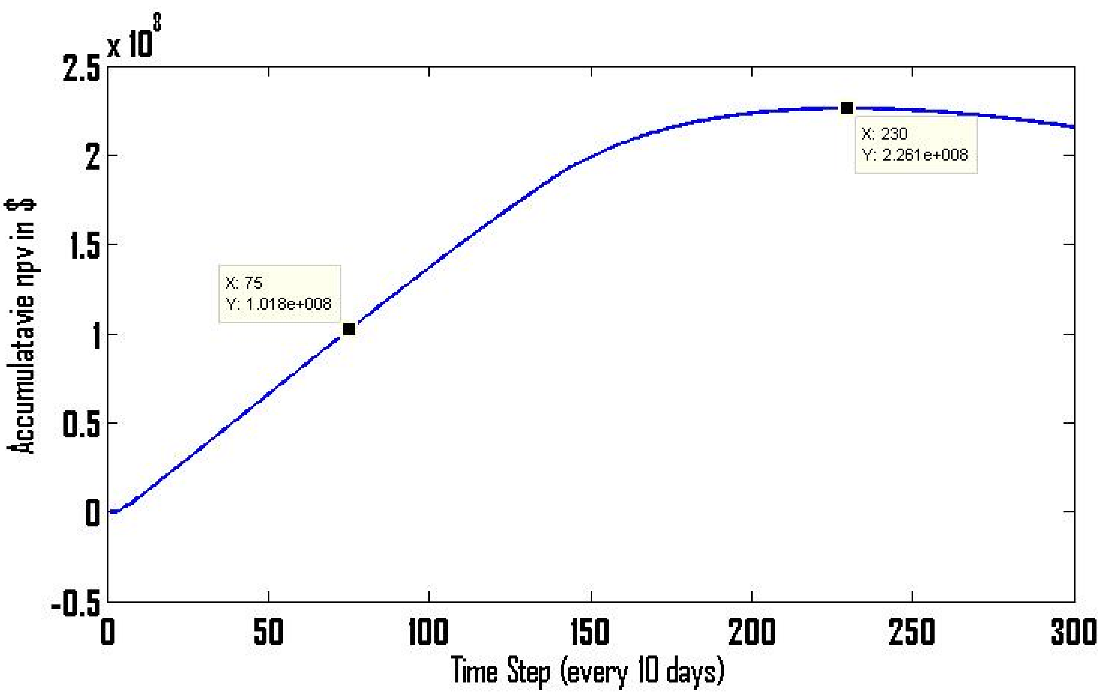

Figure 12. Accumulative *npv*; controller tries to fix theinstant *npv* at the desired setpoint

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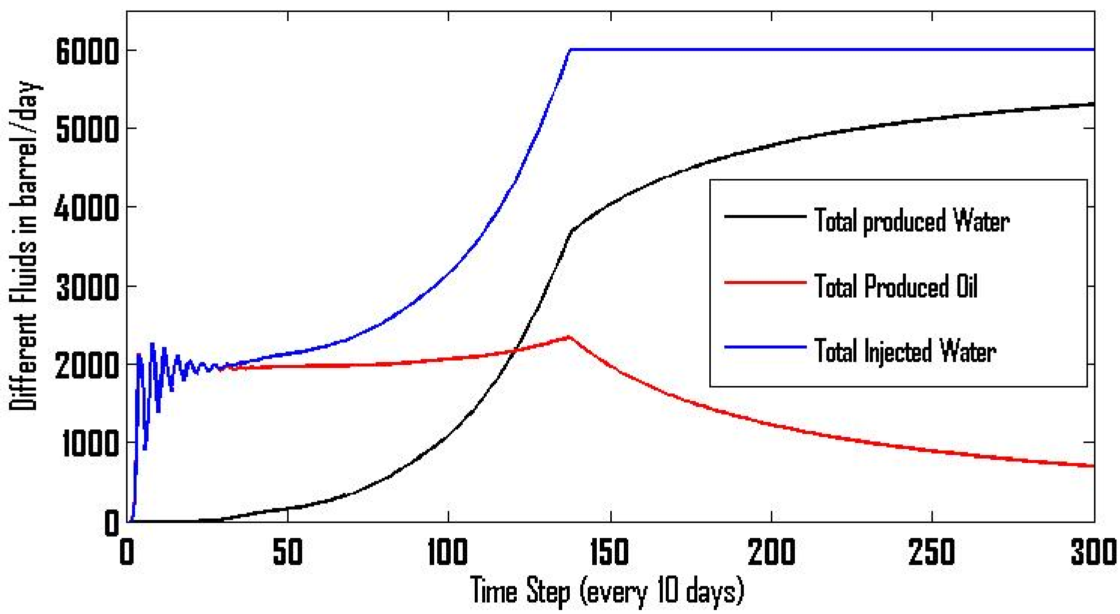

Figure 13. Total oil and water production rates; total injection rate is calculated by the controller (saturation occurs in the manipulated variable)

The suggested remedy for the above problem is re-adjusting the desired setpoint based on the productivity condition of the reservoir. This can be done by applying the explained methodology described in section 6, using data fusion technique for inferring the capability of the reservoir to produce hydrocarbon. Applying optimistic exponential *OWA* results in the fusing weights as $w_1=0.08$, $w_2=0.16$, $w_3=0.52$ and $w_4=0.25$ by which the *AWCI* can be calculated based on each well's watercut for estimating the productivity condition of the reservoir. In the first studied scenario it is assumed that for every 10% increment in the value of *AWCI*, the *npv* setpoint decrements 10% accordingly. It can be observed in Figure 14 that although reducing the setpoint value in proportion to *AWCI* rise is somehow a solution to track the profitability loss in the reservoir, the controller is still incapable to accurately fix the *npv* at the new desired value. In addition, even after time step #293 the instant *npv* becomes negative. Figure 15, Figure 16 and Figure 17 depict the accumulative *npv*, total fluid rates, and watercuts related to this scenario, respectively.

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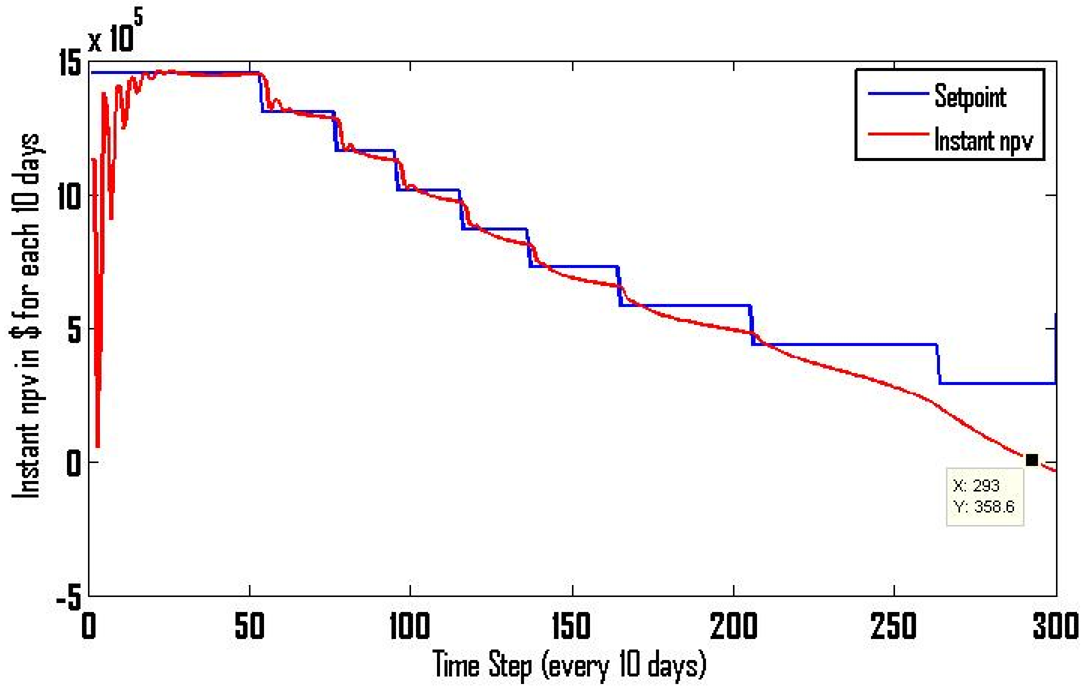

Figure 14. Instant *npv*; controller tries to fix the *npv* at the desired setpoint calculated based on *AWCI* rise

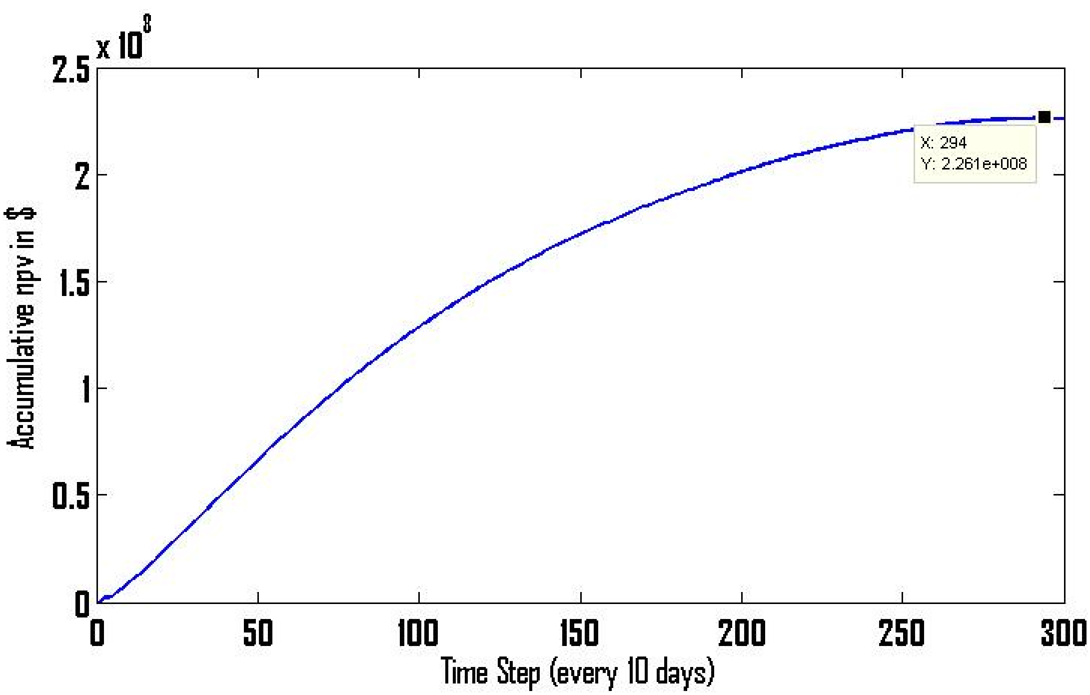

Figure 15. Accumulative *npv*; controller tries to fix the *npv* at the desired setpoint calculated based on *AWCI* rise

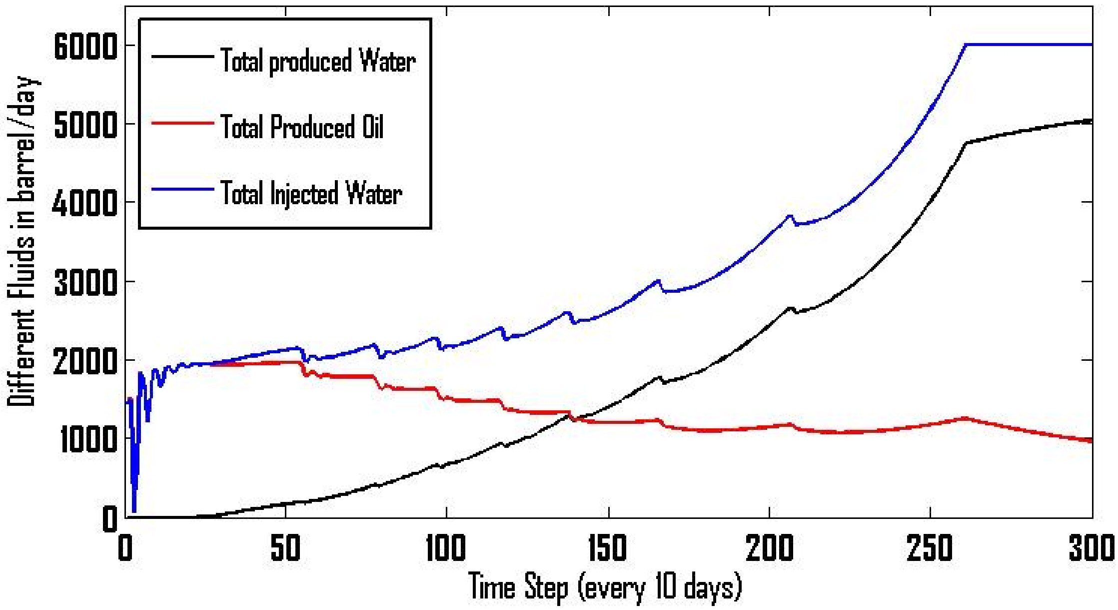

Figure 16. Total oil and water production rates; total injection rate is calculated by the controller

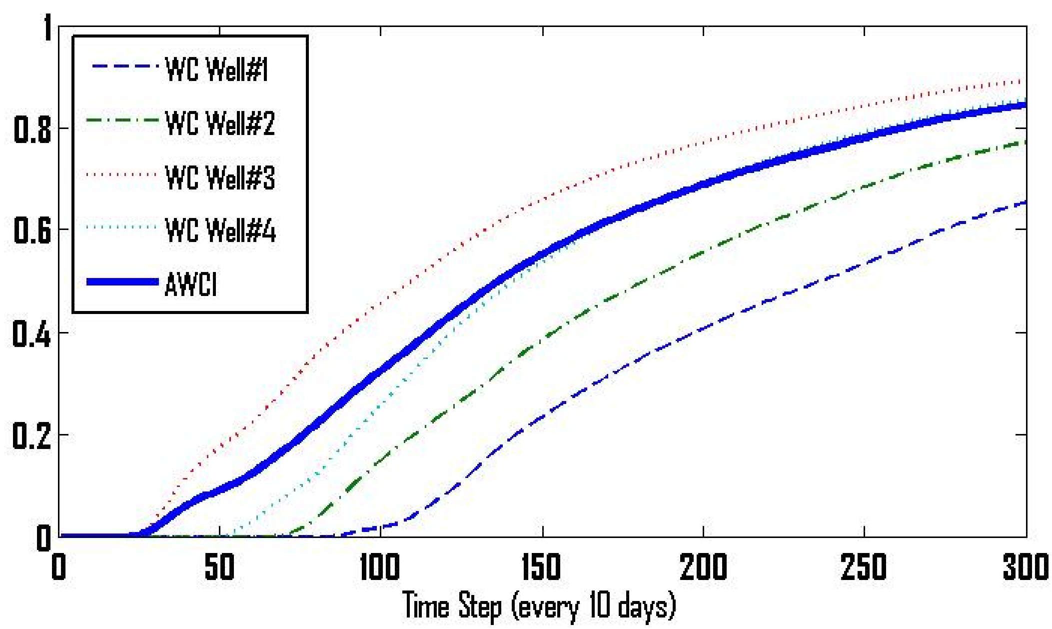

Figure 17. *AWCI* and watercut values of all producing wells

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The solution to the above dilemma is taking into account other factors which may cause profitability drop in a reservoir. It means that in contrast to linear setpoint reduction just based on *AWCI* value, the negative effect of water injection cost on *npv* computation is also considered. Based on this strategy, whenever a certain percentage of increase occurs in *AWCI*, the setpoint value decreases accordingly. By the way, the setpoint reduction steps are properly determined based on the relative influences of the effective parameters on *npv* drop. The following results demonstrate that this strategy is hopefully successful for automatically re-adjusting the setpoint value in a feasible range in accordance with the reservoir and operational conditions. As it can be observed in Figure 18, for a certain period of time, which is specified based on the production history and the relevant costs, the impact of *AWCI* rise is amplified in the setpoint drop (for this scenario: 15% setpoint reduction for each 10% rise in *AWCI*). However; after the critical time, specified in Figure 19, this effect can be attenuated which generally results in more gained profit during the reservoir life-cycle (5% setpoint reduction for each 10% rise in *AWCI*). Figure 20, represents graphs of *AWCI* as well as each producing well watercut for this scenario. In Figure 21 the trend of accumulative *npv* is observed. It can be concluded that by selecting a suitable setpoint trajectory for the instant *npv*, any feasible accumulative profit up to a desired time is achievable. This characteristic makes the developed algorithm thoroughly suitable for being applied as a profit-sharing technique in multi-lateral operational contracts. Furthermore, while Figure 22, depicts the total values of different fluids in this scenario, Figure 23 and Figure 24 illustrate oil production and water production rates of the producing wells, respectively.

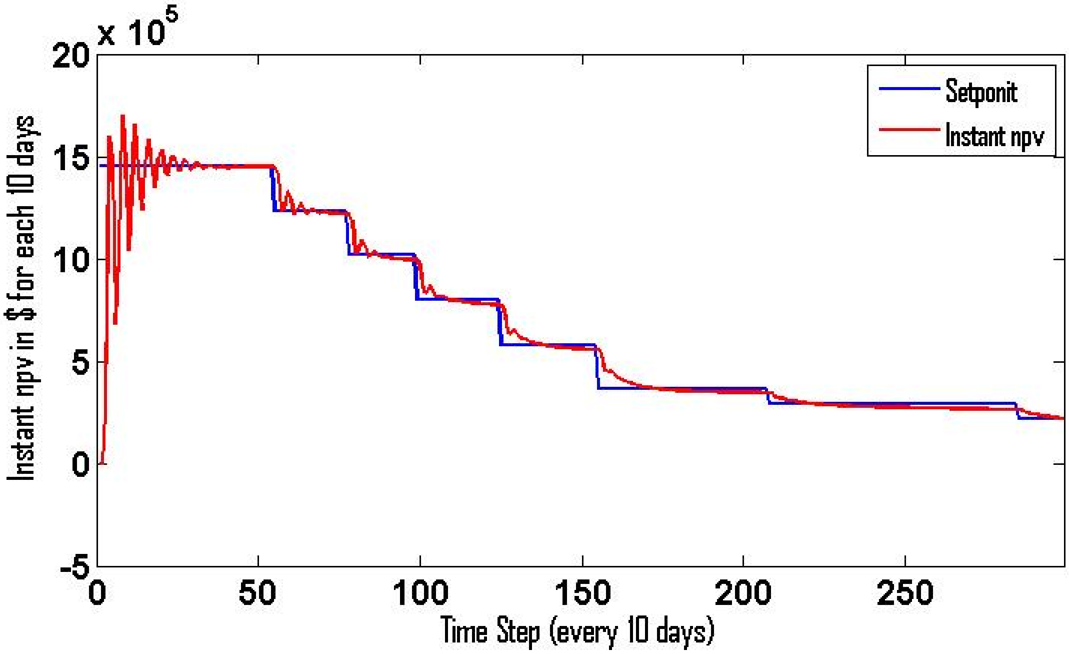

Figure 18. Instant *npv*; controller tries to fix the *npv* at the desired setpoint calculated based on *AWCI* rise as well as considering other effective terms

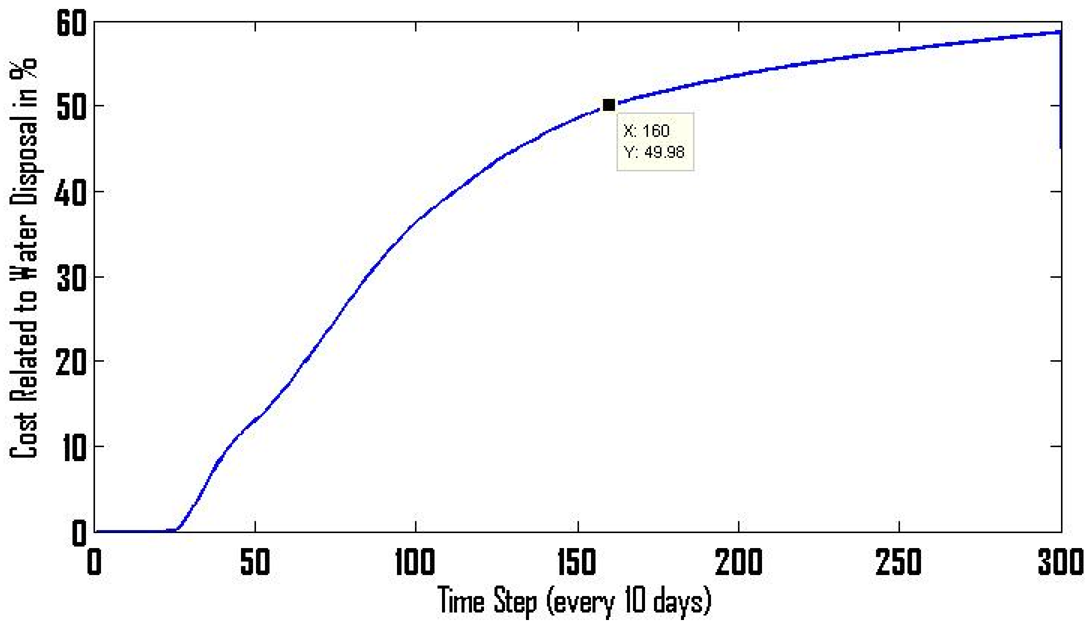

Figure 19. Critical point for deciding about amplification or attenuation of the *AWCI* impact on the value of setpoint drop

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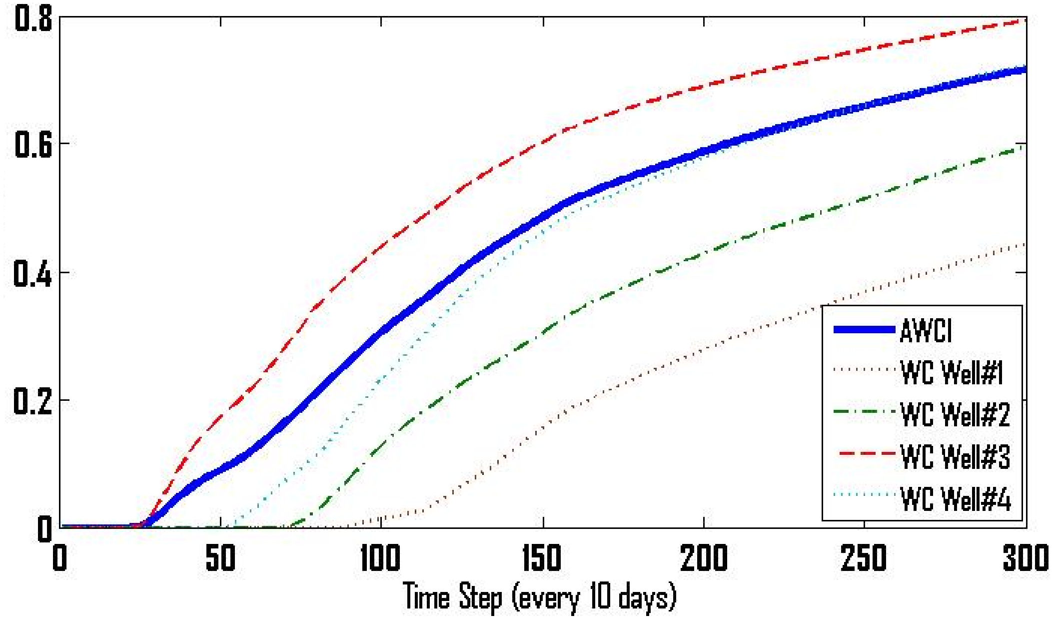

Figure 20. *AWCI* and watercut values of all producing wells

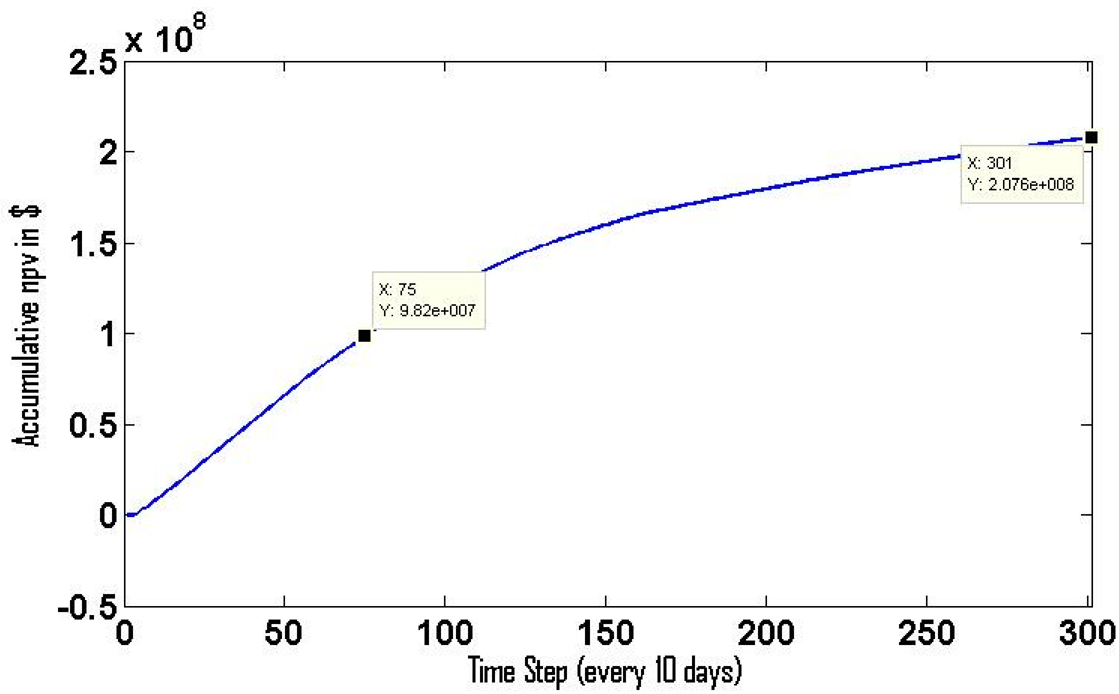

Figure 21. Accumulative *npv*; controller tries to fix the *npv* at the desired setpoint calculated based on *AWCI* rise as well as considering other effective terms

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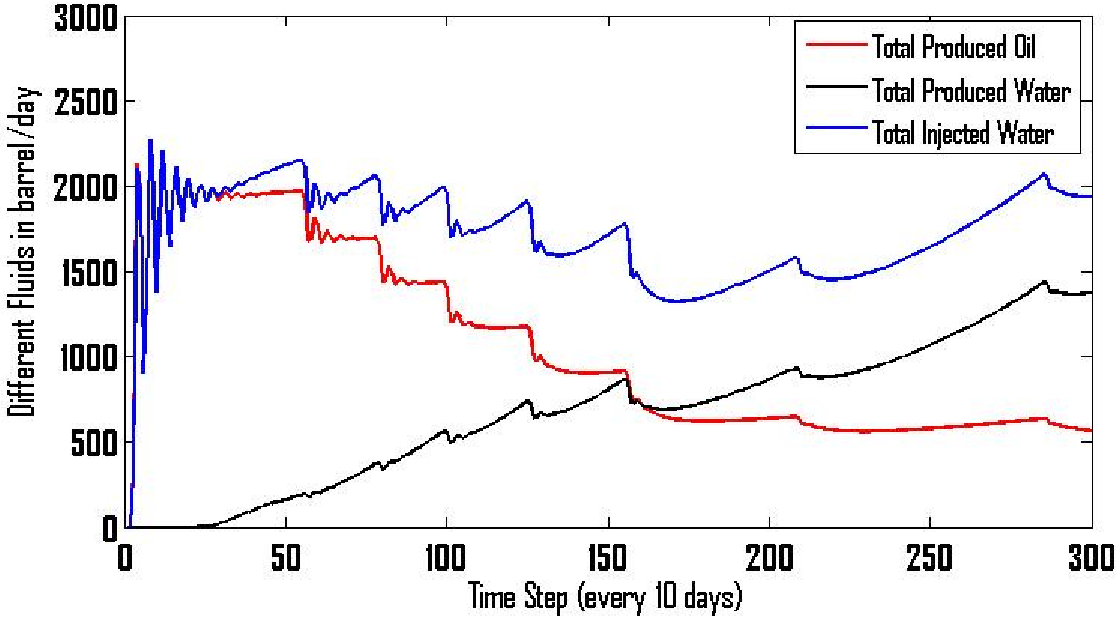

Figure 22. Total oil and water production rates; total injection rate is calculated by the controller

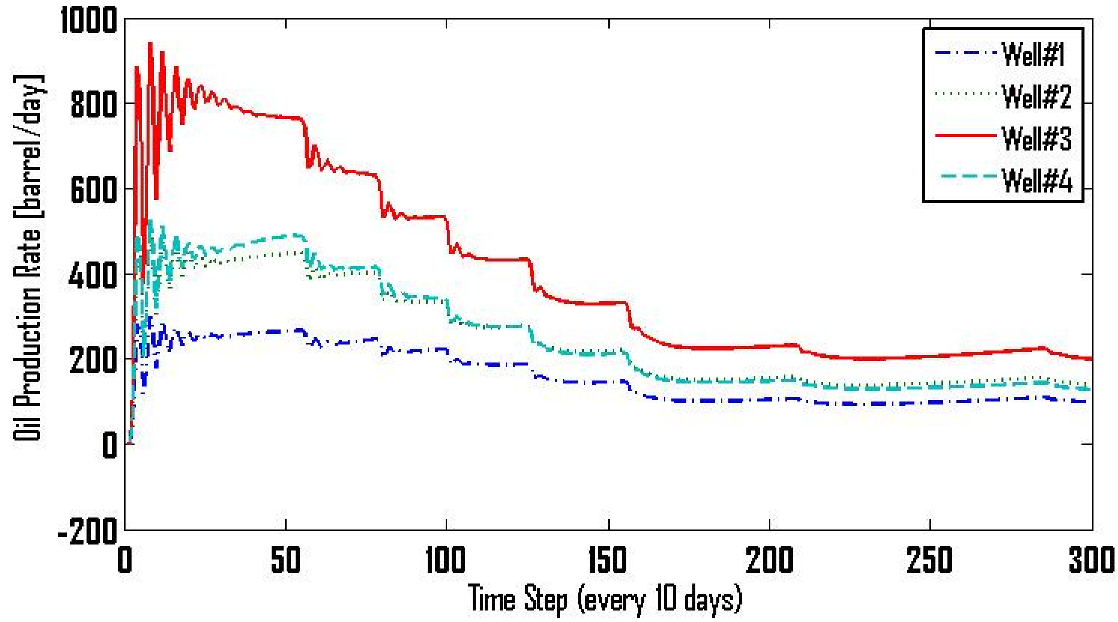

Figure 23. Oil production rates of the producing wells

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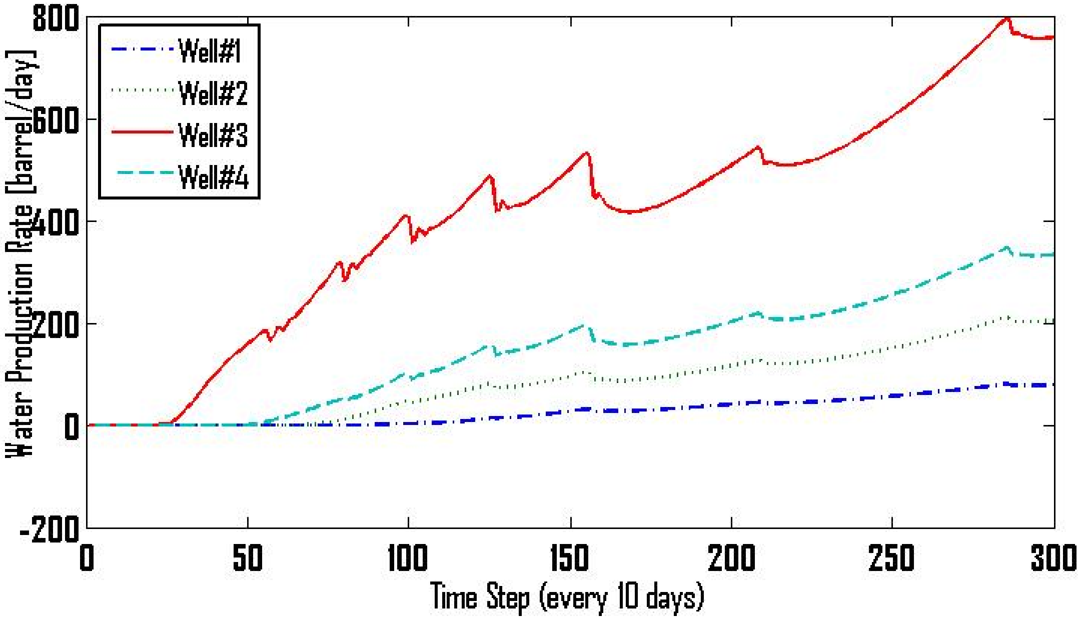

Figure 24. Water production rates of the producing wells

For the last studied scenario, variations in oil prices and operational costs have been considered. Figure 25 shows these changes which is assumed to be 15% in oil price, 20% in water disposal cost and 30% in water injection cost at the specified times. As it can be inferred from Figure 26, the developed algorithm is not only able to re-adjust the setpoint at the proper times based on the productivity condition of the reservoir, but also is able to make the *npv* value follow the feasible proposed setpoints even if the effective system parameters change during the production.

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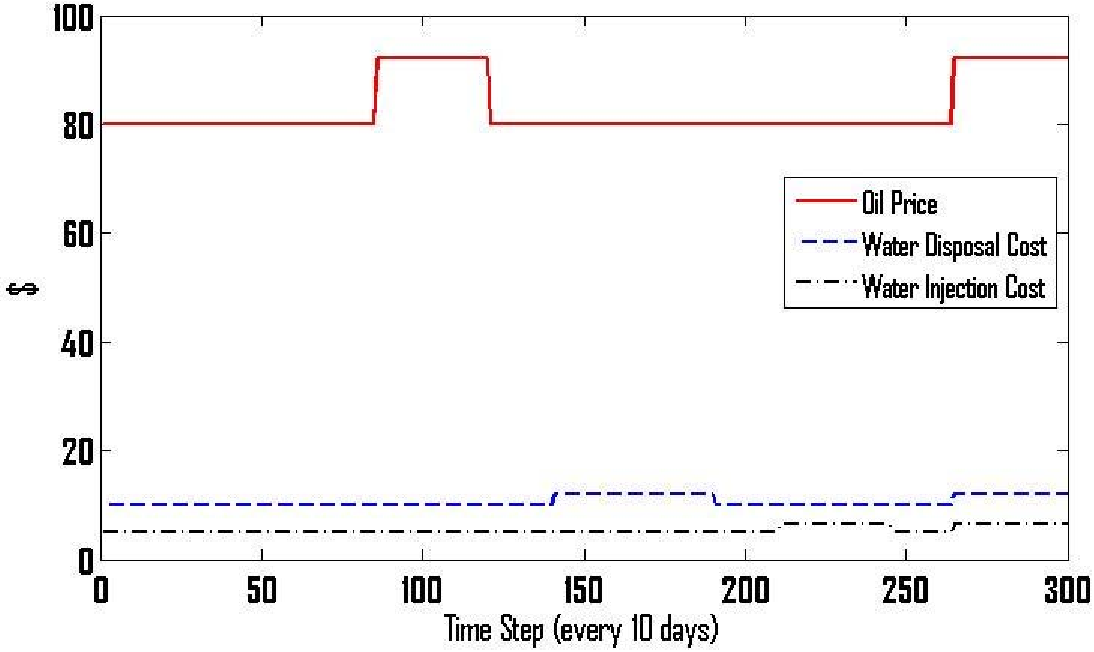

Figure 25. Profile of variations in the oil price, water disposal cost and water injection cost for the life-cycle of the reservoir

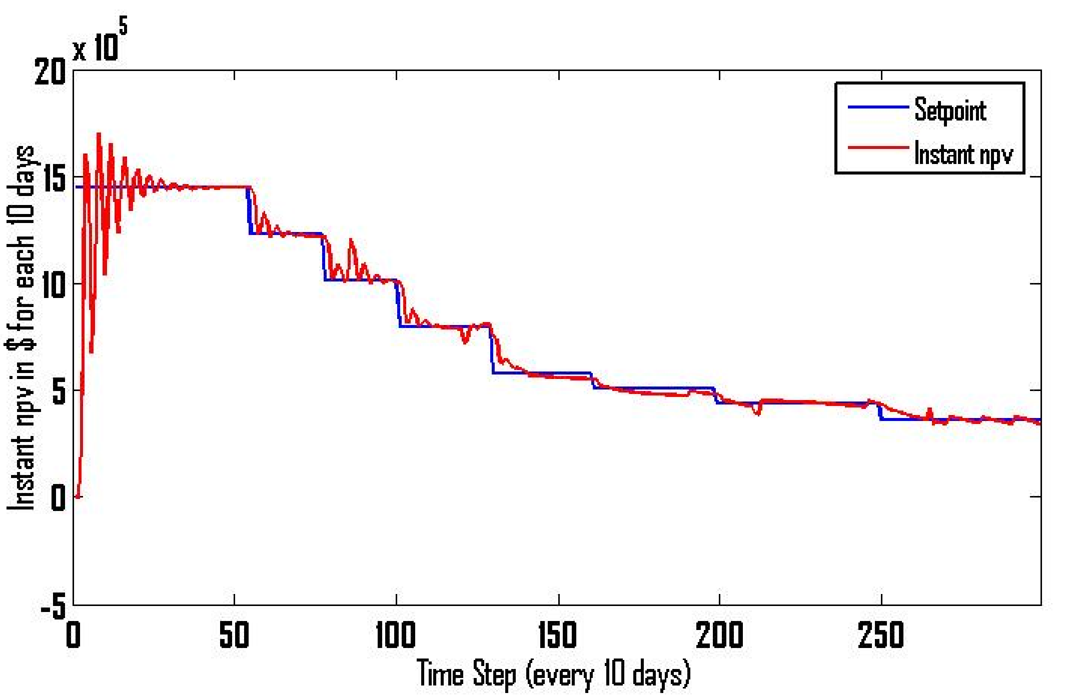

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Figure 26. Instant *npv*; controller tries to fix the npv at the desired setpoint calculated based on AWCI rise as well as considering other effective terms by successfully handling the unexpected cost/price variations

9. Conclusion

Although many optimization algorithms have been developed in recent years for achieving an efficient waterflooding strategy, most of the solutions encounter with unpredicted problems in practical applications due to the time-varying nature of hydrocarbon reservoirs and also the existence of geological and hydrocarbon market uncertainties. On the other hand, the profit sharing between the clients and contractors in different stages of field development projects dictated by various types of contracts is mostly a controversial issue. The main reason is that the reservoir may present unexpected behaviors in practice compared to the predicted results obtained in the simulation and evaluation phase. To cope with the mentioned problems, in this paper a real-time reservoir management algorithm during the waterflooding process based on well-known adaptive control techniques and using proxy reservoir modeling approach has been introduced. This methodology helps to evade from one of the common existing drawbacks which is struggling with cumbersome computations, required for either fully gradient-based or derivative-free reservoir optimization approaches. In other words, transferring the sophisticated reservoir management problem to the framework of straightforward adaptive control developed in this work is an advantage of the current contribution. The developed technique leads to more realistic results suitable for real applications while taking into account the process dynamic changes as well as compensating the unexpected disturbances. Moreover, by using self-optimizing-control (SOC) theory, it has been demonstrated that the proposed algorithm outcomes are completely optimal under the satisfaction of specific conditions. In addition, based on data fusion theory, a real-time

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condition monitoring system for estimating the productivity status of the reservoir has been designed for preventing from infeasible profit expectation during the waterflooding process by re-adjustment of the desired profit setpoints. The developed approach has been implemented and assessed for 10th SPE-Model#2 which is a popular reservoir case study. The observed results demonstrate that the proposed technique has sufficient capability to handle the nonlinearity and the time-varying dynamics of the process due to the adaptive nature of the presented algorithm for different production scenarios or contracts. In addition, the results show that any variation in the financial parameters such as oil price and operational costs are considered by the developed methodology to keep the defined profit (*npv*) at the desired value. Furthermore, by online monitoring of the introduced productivity index based on data fusion algorithm, the production gain setpoint always remains in a feasible range, taking into account the current status of the reservoir.

Acknowledgements:

We appreciate the assistance of Ms. Ladan Khoshnevisan for her useful technical comments, as well as her collaboration in finalizing this manuscript.

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