



A Proposed Model for Zonal Production Allocation of the Commingled Reservoirs

Mohamed Magdy^{a*}, Mahmoud A. Tantawy^b and Shady G. El-Rammah^b

a Khalda Petroleum Company, Egypt
b Petroleum Engineering Department, Faculty of Petroleum and Mining Engineering, Suez University, Egypt
*Corresponding author e-mail: m7mdmgdi90@gmail.com

Abstract

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Multi-layered completed wells are the norm in stacked reservoirs as part of efforts to maximize the economics of scale and lowering development costs. Across the field's production life, measures need to be in place to properly allocate the production contributed by each flow unit; for proper reservoir management practices and production enhancement efforts. Prediction of injected water distribution in commingled reservoirs is an important factor in the enhancement of water flooding conformance. PLT (Production Logging Tool) and chemical tracer are examples of effective tools in predicting water distribution, but their limitations are cost and validity for long period. Developing an enhanced model for water distribution prediction can improve the water flooding development strategy and save the cost of commercial software licenses and repetitive PLT jobs. This model could be done by using a proper programming language to build a valid mathematical model. It's necessary to gather PLT data for many fields to enhance the model accuracy by allocating the effect of different rock and fluid properties. Developing such a valid model requires a deep investigation of different factors and their weight in the model equations. Wide application using many PLT results will help to validate and develop the model. After reaching an acceptable accuracy, the model can be applied in waterflooding development projects to save PLTs cost and maximize the oil recovery. This model can help to take the right decisions upon W/F (Water Flooding) development strategy such as water shut-off, converting into injectors, and perforate/reperforate oil zones.

Introduction

Multiple reservoirs are commingled to reduce the wells count in field development [e.g., on platforms with limited space (Hussain et al. 2016) [1]. Downhole zonal flow allocation is important in developing a dynamic simulation model through history matching. Applications of zonal monitoring and control in multizone completion include limiting the production of unwanted fluid from a specific zone, preventing crossflow between reservoirs, selective testing or stimulating of each lateral, limiting drawdown in sand-prone formations, balancing zonal injection, and optimizing zonal production to depletion plan objectives.

Best practices for zonal allocation in smart wells include PLTs, ILT (Injection logging Tool), IPR (Inflow Performance Relationship) curve curve-based

allocation, permanent downhole Venturi flowmeters, rate calculation using pressure loss across ICV (Inflow Control Valve), DTS (Distributed Temperature Sensing) optical fiber, geochemical fingerprint analysis, and downhole acoustic passive listening.

Pressure loss across ICV method based on multirate flow test results look promising but absolutely requires at least partial choking of all ICVs. The biggest advantage of dP vs ICV method is non-sensitivity to transitory flow behaviour. IPR curve-based method was found to be simple to implement as well as quite robust for certain conditions. The main drawback of IPR method is its non-reliability in the transition period if ICV / Wellhead Choke positions are modified.

Another novel method is using dual downhole gauges per ICV. Zonal allocation is computed considering friction pressure loss between ICVs. This method is successfully tested and validated in a recent

water injector with ICVs. It can fit best for single phase fluid and relatively high production/injection rates. [2]

Zonal Allocation Methods

Zonal allocation by permeability and zone thickness (KH)

The allocation of commingled production could be done based on a static kH ratio. kH ratio has a lot of limitations as it eventually misleads as a result of increasing water production over time, skin build-up, and the introduction of downhole choking mechanisms on a layer basis. Coupled with inevitable well integrity issues over time, the quality and accuracy of the production allocation for these reservoirs are compromised [3].

Injection Logging (ILT)

It's a clogging technique through rigless intervention in injector wells. The survey is performed with a multisensor downhole ILT Logging Tool and interpreted with computer software such as KAPPA software. ILT is important for waterflood and gas flood management as it helps to understand fluid communication at wellbore ↔ reservoir contact [4]. PLT is for producer wells, but sometimes ILT is called PLT in injecting well. ILT objectives include:

- · Picking up the fluid injection intervals
- Estimating injection rate across each injection interval
- Cross-flows check between different formations with different pressures in flowing and shut-in conditions.
- Checking for tubing and/or casing integrity issues.

Figure 1 shows an example of ILT. The interpretation shows that water is not distributed equally between the perforated zones as the top intervals take the majority of the injected water, while the lower part takes a small amount of the injected water.

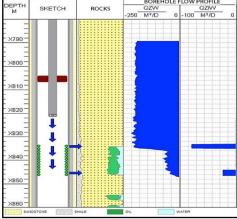


Figure 1 ILT in Water Injector.

The advantage of PLTs is that it's a simple and easy method for brownfields, but on the other side interpretations have a lot of uncertainties because PLTs are not logged for the full range of possible ICV positions; PLTs in horizontal wells are rarely logged in well-stabilized regime; coiled tubing in deviated wells have a direct impact on the inflow proportion.

Chemical water tracers

There are certain analyzes, investigations, and tests provide good knowledge about the reservoir. The tracer tests are among them, being frequently used in water injection processes. Depending on the method used, IWTT (Interwell tracer test), SWTT (Single-Well Tracer Test), or TWTT (Two-Well Tracer Test), information is obtained as related to the setting of the preferential flow path of the injected fluid, the identification of water channels, evidencing the geological barriers, determining the residual oil saturation, around the wellbore or along the tracer's path between two wells [5].

The molecule types are important for the success of water tracers. Many previous tests have failed because of the improper selection of these molecules. The most effective molecules currently used as water tracers are fluorinated benzoic acids (FBA); these molecules can be detected with very low limits of detection (LOD) using analytical techniques such as gas chromatography or ultra-high-performance liquid chromatography coupled with mass spectrometers (GC/MS and UHPLC/MS-MS, respectively) [6].

Gas chromatography fingerprint application for oil allocation

The gas chromatography fingerprint technique has the advantages of fast performance and low cost. It can be used to analyze without interruption either in the field or in the laboratory. This technique has been used successfully in such cases that conventional production logging techniques are powerless. Taking low-concentration anthracene as an internal standard, we calculated the absolute concentrations of fingerprints, initially made some experiments directly on the biodegradation of crude oils, and calculated production allocation in the oil fields. It could be applied widely for monitoring the trend of production in various oil fields [7].

Novel predictive analytics for data allocation of commingled production

This methodology details the application of a predictive analysis tool to 'S' Field's commingled production, aiming to enhance production allocation and reservoir understanding without the need for well intervention and a reduced frequency of zonal rate tests and data acquisition.

These reservoirs were further developed through intelligent wells with downhole pressure-data gauges

(PDGs) capable of transmitting real-time layer pressure and temperature data to a surveillance and analysis platform capable of converting these data into crucial information such as zonal flow rates and layer productivity index. This is done through measurement of the pressure difference of (Pannulus (Pr) – Ptubing (Pwf)) and valve opening position, S Field's real-time surveillance and analysis tool (hereafter referred to as the RTSA Tool) can calculate the zonal flow rates for each zone through the productivity index (PI) equation:

$$Q = PI \times (P_r - P_{wf}) \tag{1}$$

Where Pr is the reservoir pressure which equal to the annulus pressure Pannulus.

Pwf the flowing pressure which equal to Ptubing.

The PI for each zone is obtained from an inflow performance relationship (IPR) curve constructed from the tool's database of historical stable flow rates and annulus pressures. As the well is equipped with Inflow Control Valves (ICVs), the zonal PI value derived was later verified by zonal tests for the zonal productivity performance.

By having the zonal flow rates, an estimation of the layers' split ratios is obtained and hence a better basis for each layer's contribution in comparison to the static kH ratio. The limitation of RTSA tool is that the analysis is restricted to a single phase only, whereby the water cut for each layer is obtained through the surface well tests and the same water cut is allocated to all layers. In addition, the same split ratio is applied to both oil and water from the layers.

Allocation of the production data to its respective reservoirs is performed via a novel Multi-Phase Allocation method (MPA), considering the water production trending evolution derived from relative permeability curves for oil and water in each reservoir to calculate liquid flow rates over time. The precision of the derived rates is constrained by actual tests for zonal rates through (ICVs). This method will be compared against the existing algorithm for zonal rate allocation, utilizing pressure and temperature real-time data and input data from well tests results [3].

The MPA method is more accurate than the conventional KH methodology, for zonal allocation as MPA considers the water cut trending between reservoirs. The tool is also fully integrating a pseudosteady state rate formulation with fractional flow modeling. For each reservoir, a search engine will look for water-oil ratio (WOR) evolution type curve which honor well total phase productions. The type curve approximation (single water breakthrough) is good enough even in the case of complex multiple water breakthrough as a result of different water injection wells. This helps to reduce the uncertainty range in the zonal allocation process. MPA-derived zonal allocation results are close to the existing zonal rate calculation algorithm or the field, utilizing pressure and temperature real-time data and input data from well test results. In applying the MPA method, the

following data types from 'S' Field shallow reservoir comingled production well are being used:

- Well Top Data: gross and net pay thickness, porosity, permeability, and fluid viscosity.
- Well Production Data: wells production date and oil/water/gas production rate.
- Well Perforation Event Data: perforation, plug back, shut-in.
- PVT Table Data: pressure, oil formation volume factor, and gas formation volume factor
- Reservoir Layer Pressure Data: Validated reservoir pressure per layer and a pressure trend are created for each layer based on available pressure points.

In MPA tool, those input data will be stored in the input set in the hierarchy structure as Dataset, Field, Group, Well and Layer. Under each level, the corresponding data available will be stored. For example, well top characteristic and event history will be stored at layer (well-layer) level while well production history will be stored at the well level. Overall, the MPA method process workflow can be summarized in Figure 2 below:



Figure 2 MPA Tool Process Workflow

Zonal allocation: real-time data, advanced completion, and near-wellbore modelling

Intelligent well completion (IWCs) has been adopted by several operators worldwide since 2000. Several field cases are published by operators highlighting the key role of IWCs in managing reservoirs that resulted in increased recovery (Van Den Berg et al. 2010) [3].

The three key elements of an IWC system are downhole flow control, downhole sensors, and feed through packers. Downhole flow control, also referred to as ICVs, has multiple choke positions for controlling production from or injection to a reservoir. This method provides practical experience in developing a solution for zonal flow allocation using an advanced completion and near-wellbore (NWB) hydraulics simulator. This solution was implemented in a green offshore field development in the Middle East where three oil-producing wells completed with IWC system commingle production from multiple reservoirs [Hussain et al. (2016)] [1]. A PDHG located above the upper zone measures the tubing pressure of commingled flow to provide real-time pressure and temperature (P/T) data that were used in flow allocation. These smart wells were installed with interval control valves (ICVs) to control the commingled flow and permanent downhole gauges (PDHGs) [8].

The process begins with building the advanced completions well model based on well geometry, completion equipment, reservoir, and fluid data. An important step of the process is the calibration of the model's zonal productivity indexes using zonal and commingled flowing well tests to help reduce uncertainty in reservoir inflow calculations. The well model is then continuously updated with real-time downhole pressure data from the topmost tubingported PDHG, which is used as a dynamic boundary condition. An algorithm is developed to automate the process of matching the simulated rate with continuous surface rate measurements at any given ICV position. The ability to adjust the ICV choke setting, guided by flow allocation data, enabled the operator to perform proactive reservoir management, such as controlling the water cut, eliminating crossflow, and performing well testing. Figure 3 shows the input and output of the simulator methodology.

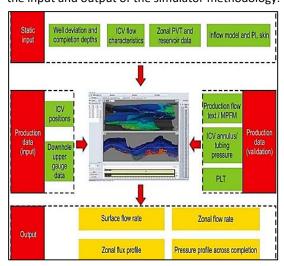


Figure 3 An Automated Workflow Methodology Input and Output.

Flow through an ICV is estimated using the generalized choke equation (Eq. 2), which relates flow rate to differential pressure across the choke, fluid mixture specific gravity, and flow coefficient.

$$Q = Cv\sqrt{\Delta p \div Sg}$$
 (2)

Where Q is flow rate in US gal/min,

C_V is flow coefficient in US gal/min/psi0.5,

 ΔP is differential pressure across the ICV flow trim in psi, and Sg is fluid mixture specific gravity (water = 1.0).

An ICV's flow trim characteristic is defined by its set of C_V values, which are derived empirically through flow loop testing, modified by computational fluid dynamics (CFD) of flow through each position's orifice, and calibrated in the field during multi-position well tests of each reservoir. The ICV flow trim's C_V values are used to generate a set of flow performance curves (Q vs. ΔP), one for each choke position, for a given fluid. These flow performance curves are then combined with the reservoir inflow model to generate a set of inflow performance relationship (IPR) curves

for all ICV choke positions. The NWB simulator is the engine for the zonal flow allocation methodology, which provides an algorithm for continuous zonal flow allocation and automated well model calibration as in figure 4.

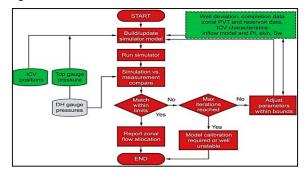


Figure 4 Zonal Flow Allocation Engineering Workflow.

The simulated model flow rates had an average error of 50 STB/D on a 5,000 STB/D total well rate, or 1% when in steady state, and an average error of 300 STB/D on a 5,000 STB/D total well rate, or 6% when in transient state.

The Proposed Model for Zonal Allocation

The area of interest for the study is located in the western desert of Egypt. Fields reserve is mainly in stratified sandstone reservoirs. The drive mechanisms for the majority of these reservoirs are depletion drive and water drive. The dominant reservoir fluid for these fields is black oil, while the rock permeability ranged between 10 to 100 mDarcy.

The wells are produced commingled to get the maximum oil production. The completion for most wells doesn't contain smart tools to monitor the downhole pressure. Only a few wells contain downhole pressure gauges to monitor the pump intake pressure.

The zonal allocation for the commingled wells is done using kH. For more accurate values, ILTs for the injector wells are done periodically to quantify the water conformance between the producing zones.

As most fields are brown fields with low daily oil production, the application of smart completions is limited to a few wells with high daily oil production. The proposed model is targeting to integrate between the available ILT and kH zonal allocation method. This is done by first using kH method to calculate zone allocation for the commingle wells. Then, these values are compared with ILT results. Definitely, there are many differences between ILT results and kH results. These different values are due to many parameters such as net pressure, oil formation volume factor, pay thickness, porosity, permeability, fluid viscosity and perforation, and frac jobs efficiency. Every single parameter of these parameters should be considered in the model to correct the kH results to match or be close in value with ILT results. The more applied ILT results in the model, the more will be the model validity. The ILT results used in the model are divided

into three proportions, the first will be used to learn and develop the model, the second proportion to validate and increase the model accuracy, and the last proportion will be used to test the model validity.

A cross years, many ILT jobs are carried out in many fields. Table 1 shows the number of ILT jobs in each field. The ILT total number exceeds 300 jobs.

Table 1 the ILT jobs for different fields

| Field | ILT No. |
|--------|---------|
| Sm | 16 |
| Sm-E | 2 |
| Hm | 4 |
| As | 21 |
| Aq | 4 |
| Ms | 9 |
| Rb | 2 |
| Rh | 9 |
| Sh-NE | 2 |
| Ym | 6 |
| Zn | 13 |
| К | 4 |
| KNE | 1 |
| KNW | 1 |
| KSE | 1 |
| KSW | 8 |
| D | 22 |
| ND | 14 |
| AZE | 1 |
| EBS | 7 |
| Ys | 55 |
| WNA | 9 |
| WNC | 26 |
| WNC200 | 9 |
| WNC300 | 17 |
| WNX | 25 |
| swq | 7 |
| WR | 11 |
| NH | 1 |
| Q | 13 |
| ВС | 21 |
| H-100 | 6 |
| H-200 | 13 |
| H-400 | 4 |
| BG | 1 |
| H-300 | 1 |
| Total | 366 |

These data will help in increasing the model accuracy as these fields are similar in their reservoir's fluid type and their drive mechanisms.

Permeability data

Permeability values are calculated from the conventional core. Special core analysis (SCAL) data can help to get more accurate values for Kw. Also, Drill stem test (DST) & Repeat formation test (RFT) data can help to get K values using the measured mobility data.

Finally, open hole logs (OHL) data (porosity, V_{sand} , V_{shale} & $V_{carbonate}$) can be correlated to calculate Kw for the commingled layers.

Clay and framework mineralogy, determined from geochemical well logging, are used with porosity to estimate the permeability of clastic formations. The mineral abundances are first combined with their individual grain densities to yield a continuous matrix density log which is combined with bulk density log to produce a very accurate porosity log. The maximum feldspar abundance is used as an indicator of textural and mineralogical maturity. The level-by-level abundances of framework grains, quartz, and feldspar, slightly enhance the estimated permeability. The porosity, textural maturity, and framework grain abundances define a maximum permeability curve as a function of porosity. The clay mineral abundances act to reduce the observed permeability from this maximum permeability curve. For a given amount of clay, kaolinite is less harmful than illite, which is less harmful than smectite. The abundances of non-clay cementing agents such as calcite also decrease the permeability, but they are less harmful than clay minerals.

These concepts are embodied in the equation:

$$K = Af * \left(\frac{3*\emptyset}{2*(1-\emptyset)}\right) * e^{sum (Bi*Mi)}$$
 (3)

Where

Af: the feldspar-dependent textural maturity term,

Mi: the abundance of the mineral (its volume), and

Bi: is a constant for the mineral.

Bi constants are positive for quartz and feldspar, negative for cements such as calcite or other carbonates, and negative for the clay minerals. Permeability is assumed to depend on porosity as described in the Kozeny-Carman equation.

The textural/mineralogy maturity term, Af, is:

Af = 4.4

Default Bi values:

Clays: Kaolinite (-4.5), Illite (-5.5), Smectite (-7.5)

Cements: Calcite (-2.5)

Framework Minerals: Quartz (0.1), Feldspars (1.0)

ILT interpretation method

The ILT is done by rigless operations on the injector wells. The flow rate is measured by a spinner reacts in different ways according to the injected water in each of the perforated zones. The row data then proceeded using Emeraude software (KAPPA). The software is used to calculate the threshold velocity of the spinner and get the interpretation results for each well.

Single zone data

Fortunately, there are some fields (e.g., Amn field) producing from one zone. The daily injection and production data can help to monitor the injected water versus the zone injectivity.

This study can help to consider skin over time and relate it with other parameters such as:

- the formation properties and tightness
- the nature of the injected water and its effect on the formation Permeability.
- The sand production effect on the perforated intervals.

The programming language for the method

There are a lot of programming languages used all over the world for processing a model with many input parameters. The programming languages are important to link these parameters to get accurate values for the model.

The programming language used here for the model is Python. Python has an advantage over other programming languages as it is an easy language, open source, and has many available libraries for machine learning. It is observed that the usage of actual measured zonal rate tests such as ILT reduces the range of uncertainty of the developed model.

The first step in the workflow to build a model requires information about the well geometry, completion equipment, reservoir characteristics, and fluid properties. The developed model is then compared or matched with the measured well flow rate using a multiphase flow meter (MPFM) at the surface and ILT. If this is within a predefined tolerance, the algorithm will accept the simulated well flow rate and report the flow allocation. Otherwise, the model will be updated by adjusting transient parameters, such as reservoir pressure, skin, or productivity index (PI) within bounds. As long as the well model remains calibrated, it can be updated with the dynamic data and downhole pressure readings for intelligent completions to continuously estimate flow allocation.

If an acceptable match of well flow rates is not possible, the algorithm might flag the well as either unstable or needing calibration. Good model calibration is necessary if any of the transient well model parameters, such as reservoir pressure, skin, water cut, and PI changes significantly. The algorithm automates the well model calibration process

whenever it detects zonal and commingled well production tests.

Model application for history matching of dynamic simulation model

The developed model can be utilized to investigate the possibility of misallocation of reservoirs production, using data such as PVT, historical production, reservoir pressures, well events, and petrophysical information for all the commingled reservoirs, then these data were inputted into the model for the re-allocation analysis of oil and water (total liquid) production. A combination of the developed model coupled with smart field technologies such as intelligent completions and analysis tools will increase the accuracy of the back allocation of multi-phase production data in commingled reservoirs.

Conclusion

The measured data at the oil fields are valuable as it costs a lot of money and is used to get the maximum oil recovery. However, due to economic limitations, many tests are canceled, and a lot of important data are missed. The smart way is to integrate the available data to get the best results. Using machine learning is helpful to link these data. In this paper, Python usage is proposed to integrate the field data and ILT interpretation to allocate production for the commingled zones. This model is helpful in getting decisions to re-complete other zones, water shut off thief zones, and optimize oil production. The benefits of a model-based approach to zonal flow allocation include non-intrusive flow measurement in cases where direct measurement using reliable downhole flow sensors is uneconomic, challenging, rangelimited, and where the risk of downhole instrumentation failure is unacceptable. Moreover, zonal flow allocation modeling, being a software-only solution, is configurable with minimum production downtime.

Conflicts of Interest

There are no conflicts to declare.

References

- [1] Hussain, A., Vega, J. C., Hassane, M. A. S., et al. (2016). Enhancing smart completion capabilities by integration with digital oil field real-time monitoring system in a green field of ADMA-OPCO. SPE-183240-MS. https://doi.org/10.2118/183240-MS
- [2] Salimov, R., & Sarsekov, A. (2017). Allocation of zonal production in smart wells: Offshore Abu Dhabi case study. SPE-188416-MS. https://doi.org/10.2118/188416-MS
- [3] Chia, M. P., Yakup, M. H., Tamin, M., et al. (2018). Application of novel predictive analytics for data allocation of commingled production in smart fields. SPE-192078-MS. https://doi.org/10.2118/192078-MS
- [4] Nafta Wiki. (n.d.). Injection Logging (ILT). Retrieved from

- http://nafta.wiki/pages/viewpage.action?pageId=32 407944
- [5] Zecheru, M., & Goran, N. (2013). The use of chemical tracers in water injection processes applied on Romanian reservoirs. EPJ Web of Conferences, 50, 02005.
 - https://doi.org/10.1051/epjconf/20135002005
- [6] Serres-Piole, C., & Preud'homme, H., et al. (2012). Water tracers in oilfield applications: Guidelines. Journal of Petroleum Science and Engineering, https://doi.org/10.1016/j.petrol.2012.08.009
- [7] Wen, Z., & Zhu, D., et al. (2005). The application of gas chromatography fingerprint technique to calculate oil production allocation of a single layer in the commingled well. *Petroleum Exploration and Development*, 32(4), 80–85. Retrieved from https://link.springer.com/content/pdf/10.1007/BF0 2871319.pdf?pdf=inline%20link
- [8] Lasrado, V., Kalyani, T., & Regulacion, R. (2017). Zonal flow allocation: Practical experience using real-time data and advanced completion and near-wellbore modeling. SPE-188051-MS.

https://doi.org/10.2118/188051-MS