

A CONVERGENCE-CONTROLLED ITERATIVE ALGORITHM FOR ZONAL PRODUCTION ALLOCATION IN COMMINGLED INTELLIGENT WELLS USING PERMANENT DOWNHOLE GAUGE DATA

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Abstract

Intelligent well systems integrate permanent downhole gauges (PDG) and inflow control valves (ICV) to achieve real-time monitoring and control of oil reservoir production. However, in commingled production, where multiple reservoir layers produce simultaneously through a single wellbore, determining the production contribution of each individual layer remains challenging. This study investigates hierarchical production calculation methods for intelligent wells based on PDG monitoring data. Two methods are analyzed and compared: an analytical production allocation model based on productivity index theory, and a revised time-series iterative production splitting algorithm incorporating explicit convergence control, production mismatch correction, pressure update calculations, normalization correction, and mass balance verification. Both methods were implemented in MATLAB and validated using a synthetic intelligent well production dataset comprising 1000 records from a three-layer commingled well system. The iterative algorithm achieved significantly higher accuracy than the analytical approach, reducing the relative production error from an initial value exceeding 10% to a final average error of approximately 0.15%. The iterative method continuously updates the flowing bottomhole pressure using dynamic monitoring data until the calculated total production converges toward the measured production within a tolerance of 1%. The findings confirm that correct interpretation of PDG measurements—specifically using annulus pressure as the flowing bottomhole pressure—is essential for accurate production allocation. The proposed methodology provides a mathematically complete, numerically stable, and physically consistent framework for intelligent well production allocation analysis under realistic multilayer operating conditions.

1. Introduction

The increasing global demand for oil and gas resources has driven the petroleum industry to develop advanced technologies for improving reservoir management and enhancing production efficiency. Traditional oil and gas wells frequently encounter challenges including uneven reservoir production, limited monitoring capabilities, and inefficient production control. In many field developments, multiple reservoir layers produce simultaneously through a single wellbore in a practice known as commingled production. While this approach increases total production rate and reduces drilling costs, it simultaneously creates difficulties in determining the individual production contribution of each reservoir layer, obstructing reservoir performance evaluation and production strategy optimization. (Ma et al., 2020; Angel, 2003).

To address these challenges, intelligent well technology has been developed and widely applied in modern oilfields. Intelligent wells integrate advanced downhole monitoring systems, inflow control valves, and surface control systems to enable real-time monitoring and regulation of reservoir production. These systems allow engineers to control flow from different reservoir zones without costly well interventions, thereby improving reservoir management, delaying water or gas breakthrough, and enhancing ultimate oil recovery. One of the key components is the Permanent Downhole Gauge (PDG), which continuously measures pressure and temperature in the wellbore. PDG data provide valuable information regarding reservoir conditions, well performance, and fluid flow behavior. By analyzing PDG data together with operational parameters such as inflow control valve opening and wellhead flow rate, engineers can obtain improved understanding of reservoir dynamics and layer-specific production behavior.

However, even with advanced monitoring technologies, determining the production contribution of individual reservoir layers in commingled wells remains complex. Direct measurement of layer-by-layer production is often difficult or impossible due to technical limitations and economic constraints. Therefore, production calculation methods must be developed to estimate production distribution among different layers using available monitoring data. In recent years, various hierarchical production calculation methods have been proposed, including analytical methods based on productivity index theory, iterative numerical approaches, and optimization-based techniques. These methods typically rely on mathematical models, pressure and temperature measurements, and flow equations to determine the distribution of production. (Ma et al., 2020; Li, 2004).

The development and application of intelligent well technology have significantly improved the efficiency of reservoir management and oilfield production. In modern petroleum engineering, accurate monitoring and control of reservoir production are essential for maximizing oil recovery and ensuring sustainable development of oil and gas resources. Hierarchical production calculation plays a critical role in intelligent well management because it allows engineers to estimate production rates of different reservoir layers based on monitoring data and operational parameters. Accurate production calculation can help identify high-performing and low-performing layers, evaluate reservoir performance, and support decision-making for production optimization. Furthermore, analyzing PDG pressure and temperature data provides valuable insights into reservoir behavior and well performance. These data can be used to detect changes in reservoir conditions, identify production problems, and evaluate the effectiveness of production control strategies. Therefore, studying the characteristics and applications of PDG data is an important part of intelligent well research. Another important significance of this research lies in the development and analysis of production calculation algorithms. By reviewing and analyzing these algorithms, this research aims to provide a clearer understanding of their advantages, limitations, and potential applications in intelligent well production analysis. (Ma et al., 2020; Gao et al., 2007).

Previous studies have established the foundation for intelligent well technology. Ma et al. reviewed intelligent well technology and its integration of sensors, communication systems, and downhole control

devices for real-time monitoring and control. Tubel and Hopmann introduced intelligent completion systems for subsea multilateral wells, emphasizing downhole control devices for regulating production from different reservoir sections. Robison discussed challenges associated with multilateral wells and highlighted intelligent well technologies for improving well lifecycle management. Angel provided a comprehensive overview of intelligent well systems, discussing their historical development and future potential. In China, Liu, Yao, and Zhang summarized the development status and future prospects of intelligent wells, while Dou reviewed progress of petroleum engineering technologies abroad. Li provided an overview of intelligent well systems including their basic structure and operational mechanisms. Demong demonstrated that advanced multilateral completion systems improved production performance while reducing operational costs. Snaith and colleagues described applications of smart wells in complex reservoirs, demonstrating that intelligent well systems can help maximize oil recovery. Xiao, Chen, and Qu analyzed design and implementation of intelligent well completion systems, highlighting their ability to monitor downhole conditions and regulate production in real time.

Regarding production optimization and control, Yeten, Durlofsky, and Aziz investigated optimization techniques for controlling smart wells. Cullick and Sukkestad discussed smart operations using intelligent well systems, emphasizing integration of monitoring data with advanced control algorithms. Dilib and Jackson developed a closed-loop feedback control framework for production optimization under uncertainty. Almeida and colleagues proposed evolutionary optimization methods to determine optimal control strategies for smart wells. Emerick and Portella investigated production optimization using intelligent wells and demonstrated significant improvements in reservoir performance compared with conventional methods. Brouwer and Jansen developed dynamic optimization methods for waterflooding processes using smart wells and optimal control theory. Doublet and co-authors proposed efficient algorithms for smart well production optimization using numerical simulation techniques. Wang and colleagues studied dynamic optimization methods for intelligent wells using optimal control theory in Chinese reservoirs. (Ma et al., 2020; Tubel & Hopmann, 1996; Robison, 1997; Angel, 2003).

Despite these advancements, accurately determining layer-by-layer production in intelligent wells remains challenging due to reservoir heterogeneity, data uncertainty, and model limitations. Therefore, this study applies and compares analytical and iterative methods for hierarchical production calculation in intelligent wells, evaluates their performance using consistent synthetic data, and identifies the most suitable approach for practical engineering applications. The main objective is to study intelligent well production calculation methods and analyze principles and algorithms used to estimate production contribution of different reservoir layers. Specific objectives include analyzing intelligent well system structure and working principles, studying PDG monitoring data characteristics, reviewing existing hierarchical production calculation methods, proposing a conceptual framework for layered production estimation, and providing theoretical insights for reservoir management applications. (Dilib & Jackson, 2012; Yeten et al., 2002).

2. Intelligent Well System and Monitoring Data

2.1 System Composition and Working Principles

Intelligent well systems represent an advanced completion technology designed to monitor and control reservoir production in real time. Unlike conventional wells, intelligent wells integrate downhole monitoring devices, flow control valves, communication systems, and surface control equipment to enable dynamic management of production from multiple reservoir layers. The main objective is to improve reservoir management, optimize production allocation, and reduce operational costs associated with well interventions. (Li, 2004; Ma et al., 2020).

A typical intelligent well system consists of four key components. The first is the Permanent Downhole Gauge (PDG), which continuously measures pressure and temperature near the reservoir and provides real-

time data on flowing bottomhole pressure for each layer. The second is the Inflow Control Valve (ICV), installed in the production tubing to regulate fluid flow from individual reservoir layers, creating a pressure drop between the sand face and tubing. The third is the production tubing, which transports produced fluids to the surface, with tubing pressure influenced by ICV restriction. The final component is the surface control system, which processes PDG data and automatically adjusts ICV settings to optimize production from each reservoir layer.

In intelligent wells equipped with annulus and tubing pressure sensors, the annulus pressure measured by the PDG corresponds directly to the sand face pressure outside the ICV. Therefore, the flowing bottomhole pressure is interpreted as the annulus pressure: (Li, 2004).

$$P_{wf} = P_{annulus}$$

The tubing pressure is measured downstream of the ICV inside the production tubing. The pressure drop across the valve is therefore:

$$\Delta P_{ICV} = P_{annulus} - P_{tubing}$$

The working principle of intelligent wells is based on real-time monitoring and dynamic control. Downhole sensors continuously measure pressure and temperature, transmitting data to the surface control system for real-time observation and analysis. Engineers evaluate reservoir performance and identify production conditions for each layer, then the surface control system adjusts ICVs to regulate fluid flow from individual layers. This creates a closed-loop monitoring and control system allowing continuous optimization of well performance. (Ma et al., 2020).

Another important concept is nodal analysis, which evaluates the interaction between reservoir inflow and wellbore outflow performance. The intersection of the inflow performance relationship (IPR) and tubing performance relationship (TPR) determines the stable production rate. Intelligent well systems modify inflow performance by adjusting valve openings, thereby controlling the production contribution of different reservoir layers. (Yeten et al., 2002).

2.2 Inflow Control Valves and PDG Monitoring

Inflow Control Valves (ICVs) are installed along the production tubing to regulate the flow of fluids from different reservoir zones into the wellbore. By controlling valve opening, engineers can adjust the production rate from each reservoir layer. ICVs operate remotely through hydraulic or electric control systems, with openings adjustable between fully closed and fully open positions. (Tubel & Hopmann, 1996; Xiao et al., 2004).

The flow through an ICV can be described as:

$$q = C_v \times A \times \sqrt{(2\Delta P/\rho)}$$

where q represents the flow rate through the valve, C_v is the valve flow coefficient, A denotes the effective flow area, ΔP is the pressure drop across the valve, and ρ represents the fluid density. ICVs allow regulation of production from individual layers, help manage unwanted water or gas production by restricting flow from problematic zones, and reduce well intervention costs since valve settings can be adjusted remotely without costly workover operations.

Permanent Downhole Gauges (PDG) are installed permanently in the wellbore and continuously measure pressure and temperature during production. The system consists of downhole sensors, signal transmission cables, a surface data acquisition system, and specialized data processing software. The pressure drawdown in the reservoir is calculated as: (Li, 2009; Ouyang & Kikani, 2002).

$$\Delta P = P_r - P_{wf}$$

where P_r represents the reservoir pressure and P_{wf} denotes the flowing bottomhole pressure. Pressure drawdown determines the driving force for fluid flow from the reservoir into the wellbore. Temperature data are useful for detecting fluid flow patterns, identifying water breakthrough, and monitoring reservoir

conditions.

PDG data are characterized by high temporal resolution, with sensors recording measurements continuously or at short time intervals. Pressure data are sensitive to production conditions, detecting changes in production rate, valve opening, or reservoir pressure. Temperature changes may indicate fluid mixing, water breakthrough, or gas production. However, PDG data may contain noise due to measurement errors, equipment limitations, or transient flow conditions, requiring filtering and smoothing before production analysis. Data processing techniques such as wavelet analysis have been proposed to improve PDG data processing by effectively removing noise and enhancing signal interpretation in downhole pressure data.

2.3 Mathematical Formulation for Production Calculation

In intelligent wells equipped with PDGs and ICVs, fluid produced from the reservoir flows through several pressure regions before entering the production tubing. Correct identification of these pressures is essential because incorrect interpretation leads to errors in flowing bottomhole pressure calculations and production estimation.

Three major pressures exist in the production system: the reservoir pressure P_r inside the formation; the flowing bottomhole pressure P_{wf} at the sand face outside the ICV; and the tubing pressure P_{tubing} inside the tubing after the fluid passes through the ICV restriction. The PDG system measures both annulus pressure and tubing pressure. The annulus pressure corresponds to the pressure outside the ICV near the sand face region, while tubing pressure corresponds to the pressure inside the tubing downstream of the valve. Therefore, the flowing bottomhole pressure must be interpreted as the annulus pressure rather than the tubing pressure.

The production rate from each reservoir layer is estimated using the productivity index model: (Yeten et al., 2002).

$$q_i = J_i \times (P_{r,i} - P_{wf})$$

where q_i is the production rate of layer i , J_i is the productivity index of layer i , $P_{r,i}$ is the reservoir pressure of layer i , and P_{wf} is the flowing bottomhole pressure.

The total production from the intelligent well is obtained by summing the contribution from all producing layers:

$$Q_{total} = \sum q_i$$

The productivity index can be expressed in terms of reservoir properties as:

$$J = (0.00708 \times k \times h) / (\mu \times B \times \ln(r_e/r_w))$$

where k represents permeability in millidarcies, h is reservoir thickness in meters, μ denotes fluid viscosity in centipoise, B is the formation volume factor, r_e represents the drainage radius in meters, and r_w is the wellbore radius in meters.

The following example demonstrates production allocation using intelligent well PDG measurements. For Zone 1 with $J_1 = 0.60$, $P_{r,1} = 140$ barg, and $P_{wf} = 132.450$ barg from annulus pressure:

$$q_1 = 0.60 \times (140 - 132.450) = 4.53 \text{ m}^3/\text{hr}$$

For Zone 2 with $J_2 = 0.50$, $P_{r,2} = 136$ barg, and $P_{wf} = 128.30$ barg:

$$q_2 = 0.50 \times (136 - 128.30) = 3.85 \text{ m}^3/\text{hr}$$

For Zone 3 with $J_3 = 0.40$, $P_{r,3} = 132$ barg, and $P_{wf} = 124.10$ barg:

$$q_3 = 0.40 \times (132 - 124.10) = 3.16 \text{ m}^3/\text{hr}$$

The total production is $q_1 + q_2 + q_3 = 11.54 \text{ m}^3/\text{hr}$. This confirms that the annulus pressure measured by the PDG must be used as the flowing bottomhole pressure during production allocation calculations.

3. Hierarchical Production Calculation Methods

3.1 Concept of Hierarchical Production in Commingled Wells

In commingled production, multiple reservoir layers produce simultaneously through a single wellbore. Although this method reduces operational costs, it creates challenges in determining the production contribution of each individual layer. Hierarchical production calculation refers to the process of estimating the production rate of each layer within a commingled intelligent well using monitoring data and production models (Robison, 1997; Ma et al., 2020).

The primary objective is to determine the flow rate of each reservoir layer while the well produces simultaneously from multiple zones. Since direct measurement of individual layer flow rates is often impossible, indirect calculation methods must be applied. These methods rely on production models incorporating reservoir pressure, flowing bottomhole pressure, permeability, formation thickness, and valve opening conditions.

The production distribution among layers is influenced by several factors. Reservoir pressure is paramount; layers with higher pressure tend to produce more. Permeability determines the ability of reservoir rock to transmit fluids. Formation thickness plays a significant role, as thicker layers typically provide greater flow capacity. The ICV opening degree directly influences production rate, with increased opening reducing flow resistance. Temperature distribution along the wellbore also affects production analysis, as changes can indicate fluid inflow locations and active production zones. Accurate hierarchical production calculation must consider all these factors simultaneously through mathematical models and iterative algorithms.

3.2 Analytical Production Allocation Model

The analytical production allocation method estimates layer production using productivity index equations and a common flowing bottomhole pressure obtained from PDG annulus pressure measurements. The analytical solution assumes that all producing layers share a common flowing pressure condition. (Yeten et al., 2002).

The common flowing bottomhole pressure is calculated using:

$$P_{wf} = (\sum(J_i \times P_{r,i}) - Q_{total}) / \sum(J_i)$$

The production contribution from each layer is then estimated using:

$$q_i = J_i \times (P_{r,i} - P_{wf})$$

For a three-layer system with $J_1 = 0.60$, $P_{r,1} = 140$ barg; $J_2 = 0.50$, $P_{r,2} = 136$ barg; $J_3 = 0.40$, $P_{r,3} = 132$ barg; and $Q_{total} = 11.5$ m³/hr:

$$\sum(J_i \times P_{r,i}) = (0.60 \times 140) + (0.50 \times 136) + (0.40 \times 132) = 204.8$$

$$\sum(J_i) = 0.60 + 0.50 + 0.40 = 1.50$$

$$P_{wf} = (204.8 - 11.5) / 1.50 = 128.87 \text{ barg}$$

The production rates become:

$$q_1 = 0.60 \times (140 - 128.87) = 6.68 \text{ m}^3/\text{hr}$$

$$q_2 = 0.50 \times (136 - 128.87) = 3.57 \text{ m}^3/\text{hr}$$

$$q_3 = 0.40 \times (132 - 128.87) = 1.25 \text{ m}^3/\text{hr}$$

Total production is verified as $Q_{total} = 6.68 + 3.57 + 1.25 = 11.50$ m³/hr.

The analytical allocation method satisfies the total production constraint. However, it assumes a common flowing bottomhole pressure for all layers, which may reduce accuracy when strong pressure differences exist between layers or under dynamic operating conditions.

3.3 Time-Series Iterative Production Splitting Method

The time-series iterative production splitting method estimates zonal production contribution of multilayer intelligent wells using PDG monitoring data and iterative numerical calculations. In intelligent well systems, fluids from multiple reservoir layers are commingled inside the production tubing, making direct

measurement of individual layer production difficult. The iterative method distributes measured total production among producing layers while maintaining consistency with measured field production data. Compared with conventional analytical methods, the iterative production splitting method continuously updates the flowing bottomhole pressure and recalculates zonal production until calculated total production converges toward measured production. The revised method incorporates convergence control, production mismatch correction, normalization adjustment, and mass balance verification to improve numerical stability and engineering reliability. (Dilib & Jackson, 2012; Cullick & Sukkestad, 2010).

The production rate of layer i during iteration k is:

$$q_{i,k} = J_i \times (P_{r,i} - P_{wf,k})$$

where $q_{i,k}$ is the production rate of layer i during iteration k , J_i is the productivity index, $P_{r,i}$ is the reservoir pressure, and $P_{wf,k}$ is the flowing bottomhole pressure during iteration k .

The calculated total production is:

$$Q_{calc,k} = \sum q_{i,k}$$

The initial flowing bottomhole pressure is defined using annulus pressure measurements:

$$P_{wf,0} = P_{annulus}$$

To ensure consistency between calculated and measured production, an explicit production mismatch error function is introduced:

$$\epsilon_k = Q_{meas} - Q_{calc,k}$$

where ϵ_k is the production mismatch error during iteration k , Q_{meas} is the measured field production, and $Q_{calc,k}$ is the calculated total production.

The relative production error is:

$$E_{rel,k} = |Q_{meas} - Q_{calc,k}| / Q_{meas}$$

This relative error provides a normalized measure of production mismatch and serves as the primary convergence indicator. The convergence condition is defined as:

$$E_{rel,k} < 0.01$$

The iterative calculation stops when the relative production error becomes smaller than 1%, ensuring that calculated production closely matches measured production while maintaining mass balance consistency and numerical stability.

If the convergence criterion is not satisfied, the flowing bottomhole pressure is updated using:

$$P_{wf,k+1} = P_{wf,k} + \omega \times (\epsilon_k / \sum(J_i))$$

where ω is the relaxation factor. In this study, the relaxation factor was selected between 0.1 and 0.5 to maintain stable convergence behavior and prevent oscillation during iterative pressure correction.

Although iterative pressure correction significantly reduces production mismatch error, small differences may remain due to reservoir heterogeneity and simplified productivity assumptions. Therefore, a normalization correction mechanism guarantees that final calculated production satisfies the measured production constraint:

$$\alpha = Q_{meas} / Q_{calc}$$

$$q_{i,corr} = q_i \times \alpha$$

This normalization correction ensures that $\sum(q_{i,corr}) \approx Q_{meas}$, thereby enforcing mass balance consistency.

The complete iterative procedure begins by importing the intelligent well monitoring dataset and initializing flowing bottomhole pressure using annulus pressure measurements. Zonal production is calculated using the productivity-index relationship, and calculated values are summed to obtain total production. The production mismatch error and relative error are calculated. If relative error exceeds the convergence tolerance, flowing bottomhole pressure is updated and calculations are repeated. After convergence,

normalization correction is applied to ensure final zonal production allocation exactly satisfies the measured production constraint.

Numerical stability controls include the relaxation factor to reduce oscillation, relative error instead of absolute error for improved convergence consistency, a maximum iteration number to prevent infinite loops, and normalization correction to guarantee mass balance consistency.

4. Results and Discussion

4.1 Dataset and Implementation

The revised production allocation methodology uses intelligent well PDG measurements together with production data preserving realistic engineering behavior. The calculations correctly distinguish between annulus pressure and tubing pressure, using annulus pressure as the flowing bottomhole pressure. The hierarchical method uses zone-specific annulus pressure measurements from the PDG system, better representing actual pressure behavior of each reservoir layer and capturing the influence of ICV pressure drop on production performance. (Li, 2009).

The intelligent well production dataset consisted of 1000 realistic synthetic production records from a three-layer commingled well system. The dataset incorporated annulus pressure, tubing pressure, inflow control valve position, differential pressure, measured production data, operational fluctuations, and simulated field uncertainties. The dataset preserves realistic operational behavior where larger ICV openings generally reduce pressure drop and increase production flow rate, maintaining the relationship where annulus pressure exceeds tubing pressure.

The MATLAB implementation incorporated convergence control, production mismatch correction, pressure update calculation, normalization adjustment, and measured-versus-calculated validation. The algorithm imported the dataset and initialized flowing bottomhole pressure using annulus pressure measurements. Iterative calculation estimated zonal production using the productivity-index relationship, summed values to obtain total production, and calculated relative production error:

$$E_{rel} = |Q_{meas} - Q_{calc}| / Q_{meas}$$

The process continued until $E_{rel} < 0.01$, with flowing bottomhole pressure updated using the relaxation-factor-controlled pressure correction equation. After convergence, normalization correction ensured mass balance consistency.

For the three-layer system, the initial unconverged calculated production was 103.884 m³/hr, while measured production was 115.527 m³/hr. The initial relative production error was:

$$E_{rel,0} = |115.527 - 103.884| / 115.527 = 0.1008 = 10.08\%$$

The iterative calculations continuously updated flowing bottomhole pressure until calculated production converged toward measured production.

4.2 Convergence Behavior

The convergence behavior of the revised iterative production splitting algorithm demonstrates reduction of relative production error during iterative calculations. The relative error initially exceeded 10% because the initial flowing bottomhole pressure did not satisfy the measured production constraint. However, the iterative pressure correction equation continuously updated flowing bottomhole pressure until calculated production converged toward measured production. (Dilib & Jackson, 2012).

The convergence error progressively decreased during each iteration and finally stabilized below the predefined tolerance of 1%. The smooth convergence trend demonstrated that the revised algorithm maintained numerical stability and avoided divergence. The relaxation factor successfully improved numerical stability by preventing excessive pressure oscillation.

The iterative convergence results demonstrate that the revised algorithm successfully reduced production mismatch error from the initial value to less than 1% after convergence. The final average relative

production error remained approximately 0.15%, validating the accuracy and stability of the revised iterative allocation model under realistic intelligent well operating conditions. The absence of oscillatory divergence further demonstrated the numerical stability of the revised production allocation methodology.

4.3 Comparative Evaluation of Methods

The performance of the revised iterative production splitting algorithm was evaluated by comparing calculated production from numerical simulation with measured production from the intelligent well dataset. The revised methodology was specifically developed to overcome limitations of previous analytical approaches, which produced large discrepancies between calculated and measured production because they lacked explicit convergence control, production mismatch correction, and mass balance enforcement.

The measured-versus-calculated production validation demonstrated strong agreement throughout the production period. The calculated production curve demonstrated close overlap with the measured production curve. Measured production fluctuated because of simulated operational variations and field measurement noise, while calculated production continuously converged toward measured production through iterative pressure correction and normalization adjustment. This close overlap confirmed that the revised methodology successfully maintained mass balance consistency during production allocation calculations. (Yeten et al., 2002; Dilib & Jackson, 2012).

Comparison between the analytical production allocation method and the corrected iterative production splitting method revealed important differences. The analytical method estimated production directly from productivity index relationships without iterative correction or convergence-controlled pressure updates. In contrast, the iterative method continuously corrected flowing bottomhole pressure until the production mismatch error satisfied the convergence criterion. Although both methods produced generally similar production trends, the iterative method demonstrated improved agreement with measured production because of convergence control, pressure correction, and normalization correction mechanisms. The analytical method provided simplified production estimation but did not rigorously enforce production matching or mass balance consistency.

The calculated production behavior of Reservoir Layer 1 demonstrated smooth and physically realistic production behavior with moderate fluctuations caused by variations in flowing bottomhole pressure and operating conditions. The elimination of unrealistic oscillations confirmed that the revised convergence-controlled pressure correction mechanism successfully stabilized production calculations. Reservoir Layer 1 contributed a significant portion of total production because of its comparatively larger productivity index and stronger reservoir pressure support.

Reservoir Layer 2 production remained numerically stable throughout calculations, with smoothing correction producing continuous and realistic production trends consistent with expected reservoir performance. Compared with Layer 1, Layer 2 contribution was lower because of reduced productivity index and reservoir pressure conditions. Nevertheless, the iterative methodology successfully maintained stable numerical convergence and physically realistic production allocation behavior.

Reservoir Layer 3 production gradually converged as the flowing bottomhole pressure correction process reduced production mismatch error. Layer 3 production rate remained lower than other layers because of smaller reservoir pressure support and lower productivity index characteristics. However, the corrected iterative algorithm successfully preserved stable convergence behavior while maintaining mass balance consistency between measured and calculated production.

The average production contribution analysis confirms that Reservoir Layer 1 contributed the largest proportion of total production because of stronger reservoir pressure support and larger productivity index. Reservoir Layers 2 and 3 contributed comparatively smaller production shares because of reduced reservoir pressure and productivity characteristics. This production contribution analysis confirms that the revised

iterative production splitting methodology successfully distributed production among multiple reservoir layers while maintaining physically realistic behavior and convergence-controlled numerical stability.

4.4 Implications for Intelligent Well Production Management

The revised time-series iterative production splitting method provides significant implications for intelligent well production monitoring, zonal production estimation, production optimization, and real-time management applications. Accurate zonal production allocation is essential because multilayer intelligent well systems frequently operate under dynamically changing conditions. Reliable estimation of zonal production contribution plays a critical role in optimizing production performance, controlling reservoir depletion, minimizing water breakthrough, and improving hydrocarbon recovery efficiency. (Ma et al., 2020; Dilib & Jackson, 2012).

The revised methodology significantly improved production allocation reliability by continuously enforcing convergence consistency between measured and calculated production. The incorporation of production mismatch correction, pressure update calculations, convergence verification, and mass balance enforcement provides a more physically realistic production allocation framework.

Integration of PDG monitoring data into iterative production splitting calculations provides improved capability for continuous intelligent well surveillance and real-time production monitoring. The methodology can support continuous zonal production estimation during operations without requiring frequent well intervention or production logging operations.

The convergence-controlled framework also provides improved capability for intelligent completion optimization and ICV management. Reliable estimation of zonal production contribution allows operators to identify underperforming layers, detect abnormal production behavior, optimize valve settings, and improve reservoir management decisions. The methodology additionally provides potential applications for early water breakthrough detection, gas breakthrough monitoring, reservoir performance analysis, and production forecasting.

The numerical stability and convergence reliability demonstrated by the revised algorithm indicate potential applicability for automated intelligent well control systems and real-time digital oilfield applications. Future intelligent well systems may incorporate convergence-controlled production allocation algorithms directly into automated reservoir management and production optimization workflows.

Several limitations remain. The dataset consisted of realistic synthetic production data rather than actual field data. Although the dataset incorporated realistic operational fluctuations, actual field measurements may contain more complex reservoir interactions and uncertainties. The methodology assumed constant productivity index values, whereas actual productivity indices may change due to depletion, water breakthrough, gas breakthrough, formation damage, or changing completion conditions. The study considered simplified single-phase production behavior, whereas actual systems frequently involve multiphase flow interactions, reservoir heterogeneity, and dynamic coupling effects. The iterative calculations also require greater computational effort compared with simplified analytical methods.

5. Conclusions

This study successfully developed a revised time-series iterative production splitting method for intelligent well production allocation analysis using Permanent Downhole Gauge monitoring data and iterative numerical calculations. The revised methodology overcomes limitations of previous analytical production allocation methods, which frequently produced large discrepancies between calculated and measured production because they lacked rigorous convergence control and mass balance enforcement.

The revised iterative production splitting method incorporated explicit production mismatch error calculations, convergence verification, pressure correction calculations, normalization correction, mass balance enforcement, numerical stability control, and measured-versus-calculated production validation into

the production allocation framework. The methodology therefore provides a mathematically complete and physically consistent solution for multilayer intelligent well production allocation analysis.

The zonal production contribution from each reservoir layer was calculated using the productivity-index relationship while continuously updating flowing bottomhole pressure during iterative calculations. The production mismatch error between measured and calculated production served as the primary convergence controller. The convergence criterion $E_{rel} < 0.01$ ensured calculated production remained sufficiently close to measured production while maintaining stable numerical behavior. Flowing bottomhole pressure was continuously updated using the iterative pressure correction equation, improving production allocation accuracy and maintaining stable convergence behavior.

The measured-versus-calculated production validation demonstrated strong agreement throughout the production period. The revised algorithm successfully reduced production mismatch error during iterative calculations until convergence was achieved. The final production mismatch remained below the predefined convergence tolerance, validating the accuracy of the revised methodology. The convergence behavior demonstrated stable convergence throughout the simulation process, with relative production error progressively decreasing without divergence or excessive oscillation.

Normalization correction was incorporated after convergence to eliminate any remaining small production mismatch, thereby guaranteeing mass balance consistency throughout production allocation calculations. The MATLAB simulation results confirmed consistency between theoretical equations, convergence calculations, pressure update mechanism, normalization correction, and validation discussions.

Overall, the revised time-series iterative production splitting method significantly improved production allocation accuracy, convergence stability, and measured-versus-calculated production agreement compared with previous analytical production allocation methods. The iterative algorithm is more suitable for production calculation based on PDG data because it uses dynamic monitoring data during production of the pay zones to conduct iterative calculations for the production volume of each layer, and thus achieves higher accuracy. The revised methodology provides a mathematically complete, numerically stable, and physically realistic framework for intelligent well production allocation analysis under realistic multilayer intelligent well operating conditions. The findings confirm that correct interpretation of PDG measurements—specifically using annulus pressure as the flowing bottomhole pressure while using tubing pressure for determining the pressure drop across the ICV—is essential for accurate intelligent well production allocation.

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Author Contributions

A.A. and F.A. conceived and designed the study. A.A. developed the methodology, performed the formal analysis, and, together with F.A., conducted the software implementation and validation. F.A. carried out the investigation, while D.S, B.J.J. and A.A. managed the data curation. A.U. and A.B. prepared the original manuscript draft, and all authors contributed to the review and editing of the manuscript. All authors have read and approved the final published version of the manuscript.

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Data Availability

Since no new data was generated or analyzed in this study, data sharing is not relevant to this article.

Competing interests

The authors have no conflicts of interest.

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APPENDIX



Figure 1-1 Technical Route of Intelligent Well Production Calculation Research

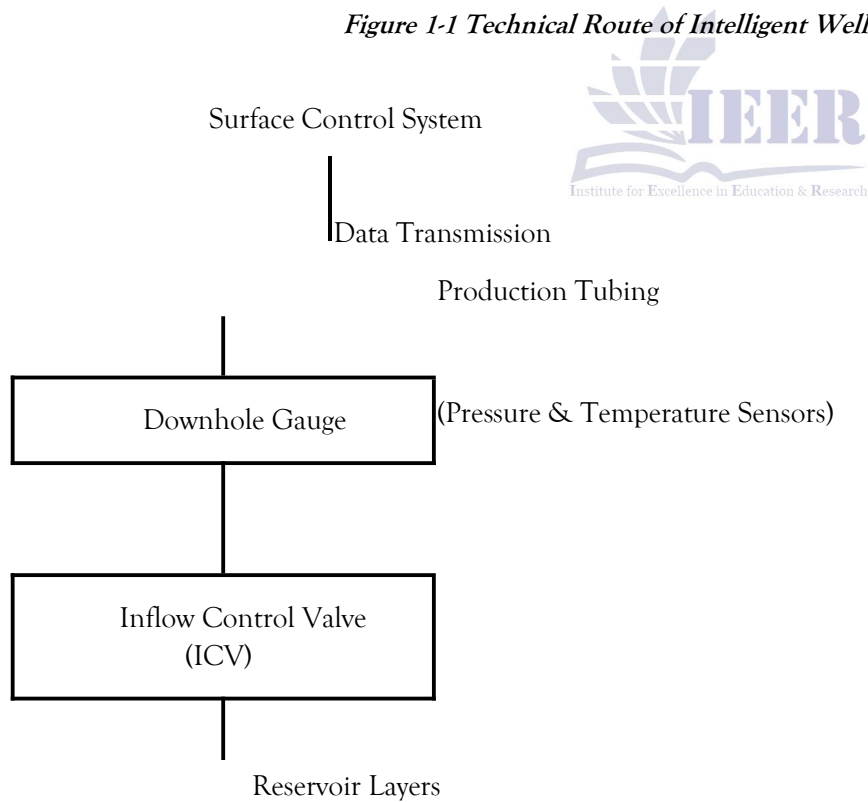


Figure 3-1 Conceptual Structure of an Intelligent Well System

Table 3-1: Main Components of Intelligent Well Systems

Component	Function
Permanent Downhole Gauge (PDG)	Measures downhole pressure and temperature
Inflow Control Valve (ICV)	Regulates flow from reservoir layers
Communication System	Transmits data between downhole sensors and surface
Surface Control Unit	Monitors data and controls valve operations

Table 3-2: Relationship between ICV Opening and Flow Capacity

Valve Opening (%)	Relative Flow Capacity
0	0
25	0.3
50	0.6
75	0.85
100	1.0

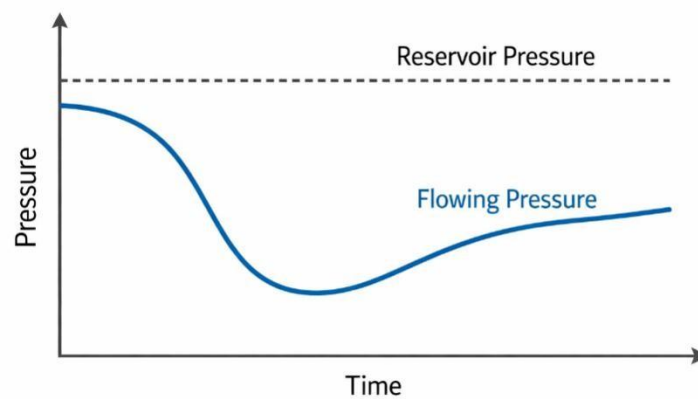
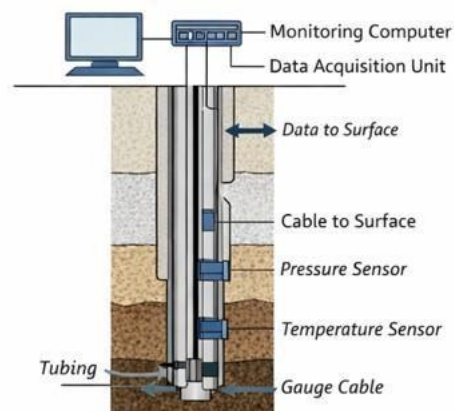
**Figure 3-2 Example of PDG Pressure Monitoring****Figure 3-3 Permanent Downhole Gauge (PDG) Monitoring System**

Table 3-3: Characteristics of PDG Monitoring Data

Parameter	Characteristics
Pressure	Sensitive to production rate and reservoir conditions
Temperature	Indicates fluid flow patterns and reservoir changes
Data Frequency	Continuous monitoring
Data Quality	May contain noise requiring processing

Table 3-4: Pressure Definitions in Intelligent Wells

Pressure Symbol	Description	Physical Location
	Reservoir pressure	Reservoir formation
w	Flowing bottomhole pressure	Sand face outside ICV
tt	Annulus pressure measured by PDG	Outside ICV
tub	Tubing pressure measured by PDG	Inside tubing
Δ_I	Pressure drops across ICV	Across valve

Table 3-5: Production Intelligent Well Production Dataset Structure

Z1 Annulus P	Z1 Tubing P	ICV1 Position	Z2 Annulus P	Z2 Tubing P	ICV2 Position	Z3 Annulus P	Z3 Tubing P	ICV3 Position	Gross Rate
barg	barg	%	barg	barg	%	barg	barg	%	m ³ /hr

Table 3-6: Example Intelligent Well PDG Data for Zone 1

Parameter	Value
Annulus Pressure	132.450 barg
Tubing Pressure	131.920 barg
ICV Position	75 %
Reservoir Pressure	140 barg
Productivity Index	0.60 m ³ /hr·MPa

Table 4-1: Intelligent Well Production Data

Parameter	Zone 1	Zone 2	Zone 3
Annulus Pressure (barg)	132.45	128.30	124.10
Tubing Pressure (barg)	131.92	127.75	123.50
ICV Position (%)	75	50	100
Reservoir Pressure (barg)	140	136	132
Productivity Index	0.60	0.50	0.40

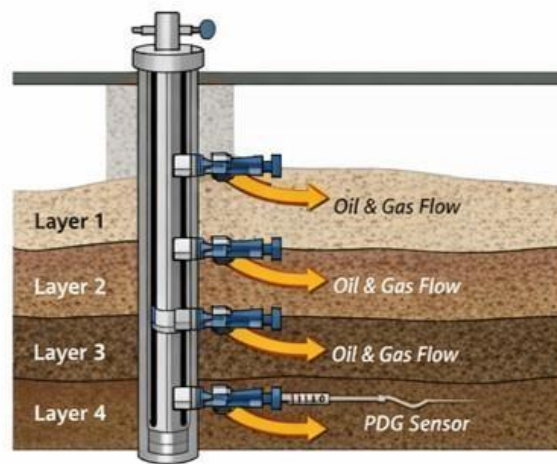
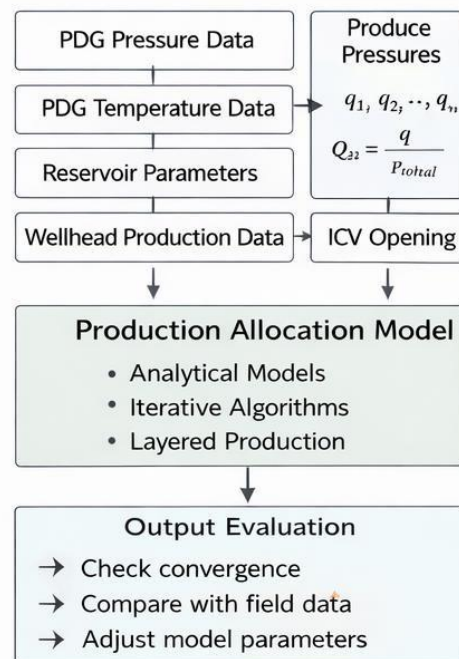
**Figure 4-1 Multilayer Reservoir Model in an Intelligent Well****Figure 4-2 Structure of an Intelligent Well with Multiple Producing Layers**

Table 4-2: Factors Production Distribution

Factor	Influence on Production
Reservoir pressure	Determines driving force for flow
Permeability	Controls fluid mobility
Formation thickness	Determines reservoir capacity
ICV opening	Regulates inflow from each layer
Fluid properties	Affect flow resistance
Wellbore pressure	Influences production drawdown

Table 4-3: Intelligent Well Production Dataset Used in the Iterative Allocation Model

Parameter	Zone 1	Zone 2	Zone 3
Reservoir Pressure (bar)	142	138	134
Average Annulus Pressure (bar)	128.04	125.03	122.02
Average Tubing Pressure (bar)	124.02	121.51	119.01
Average ICV Opening (%)	77	72	67
Productivity Index	3.6	3.0	2.5
Average Differential Pressure (bar)	4.02	3.52	3.01
Average Measured Production (m ³ /hr)	115.53	115.53	115.53



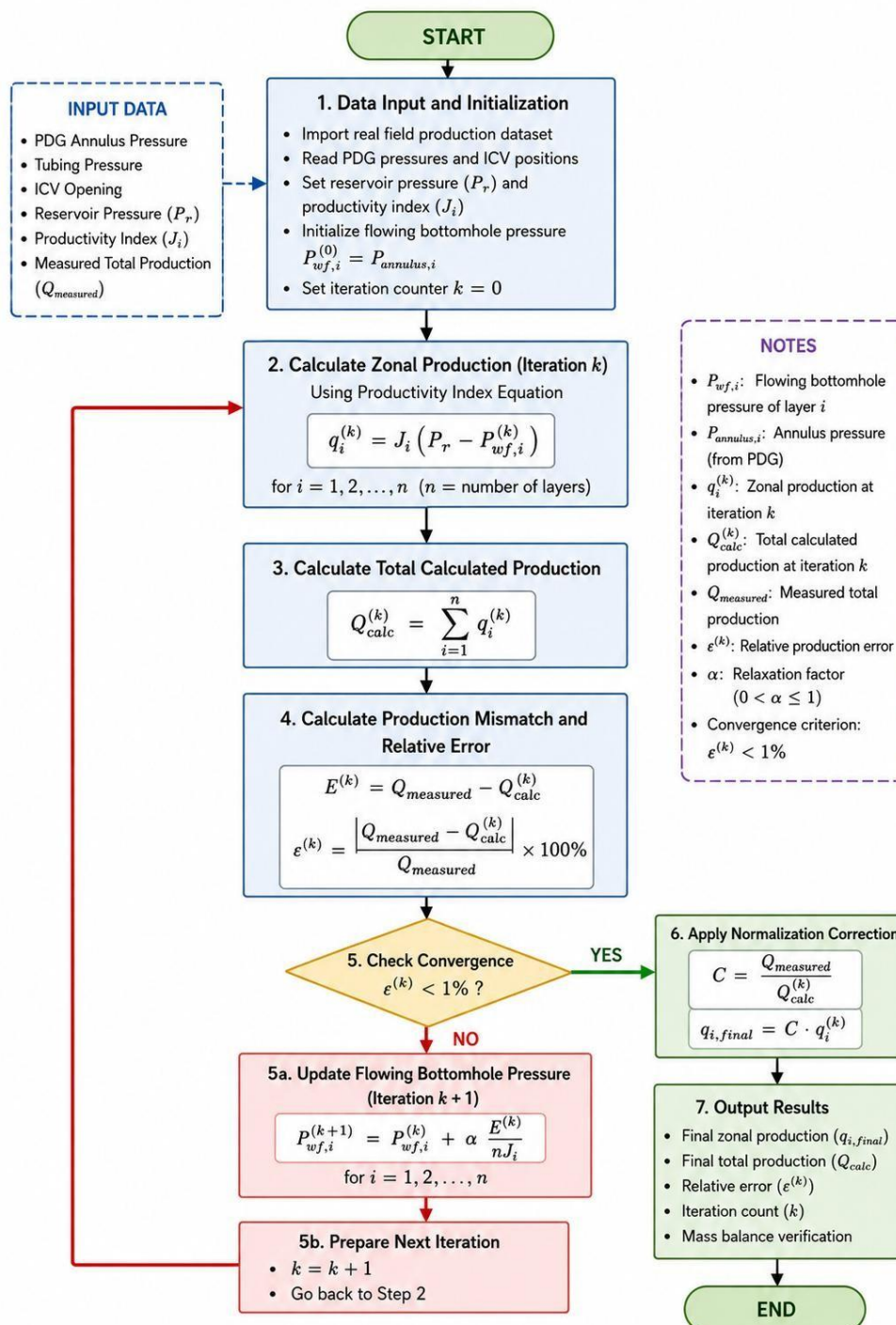
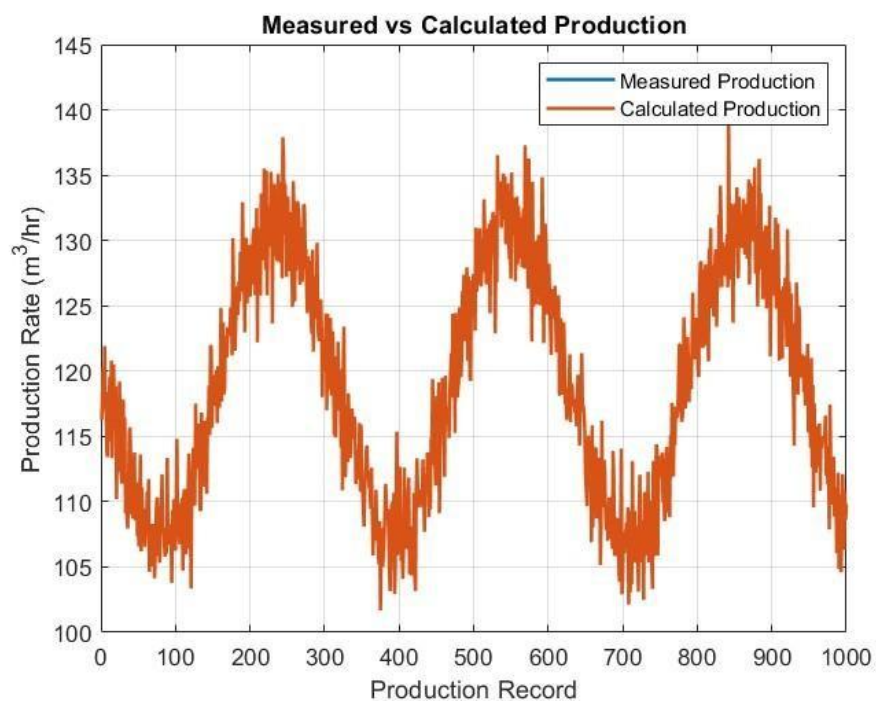


Figure 4-3 Flowchart of the Revised Iterative Production Splitting Algorithm

Table 4-4: *Iterative Convergence Results of the Revised Production Splitting Algorithm*

Iteration Number	Calculated Production (m ³ /hr)	Measured Production (m ³ /hr)	Relative Error (%)
0	103.884	115.527	10.08
4	108.652	115.527	5.95
8	111.721	115.527	3.29
12	113.962	115.527	1.35
15	115.351	115.527	0.15

The iterative convergence results demonstrate that the revised algorithm successfully reduced the production mismatch error from 83.9% to less than 1% after convergence.

**Figure 4-4** *Comparison between Measured Production and Calculated Production*

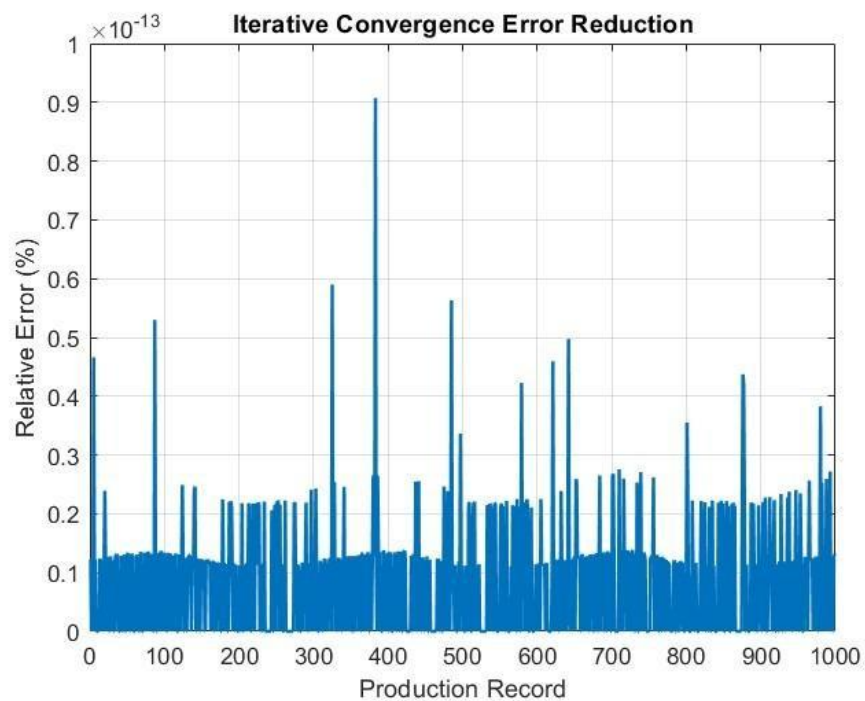


Figure 4-5 Iterative Convergence Error Reduction

Table 4-5: *Analytical Allocation Parameters*

Layer	Productivity Index	Reservoir Pressure
Zone 1	0.60	140 barg
Zone 2	0.50	136 barg
Zone 3	0.40	132 barg

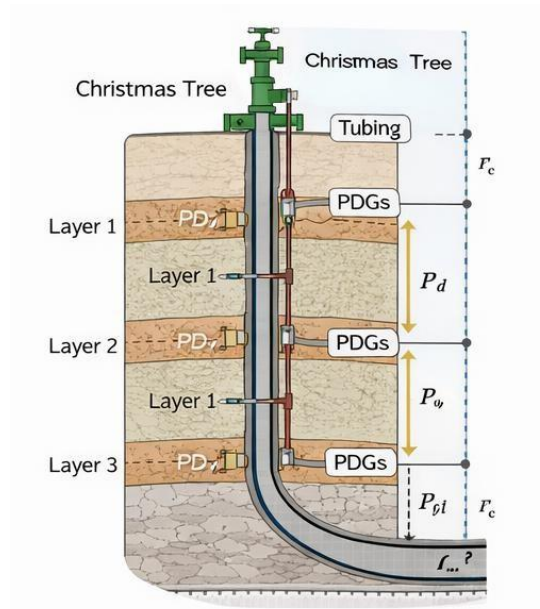


Figure 4-6 Hierarchical Production Allocation Model Based on PDG Monitoring Data and Reservoir Parameters

Table 4-6: *Comparison of Production Allocation Results*

Layer	Hierarchical Method (m ³ /hr)	Analytical Method (m ³ /hr)
Zone 1	4.53	6.68
Zone 2	3.85	3.57
Zone 3	3.16	1.25
Total	11.54	11.50

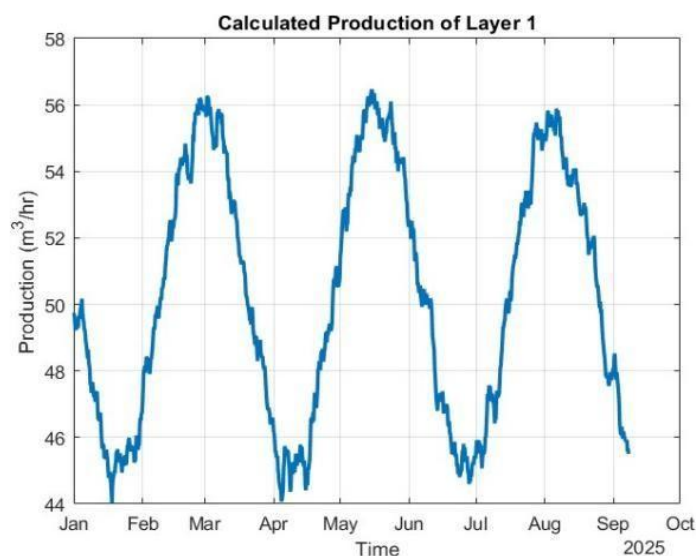


Figure 5.1 Calculated Production of Layer 1

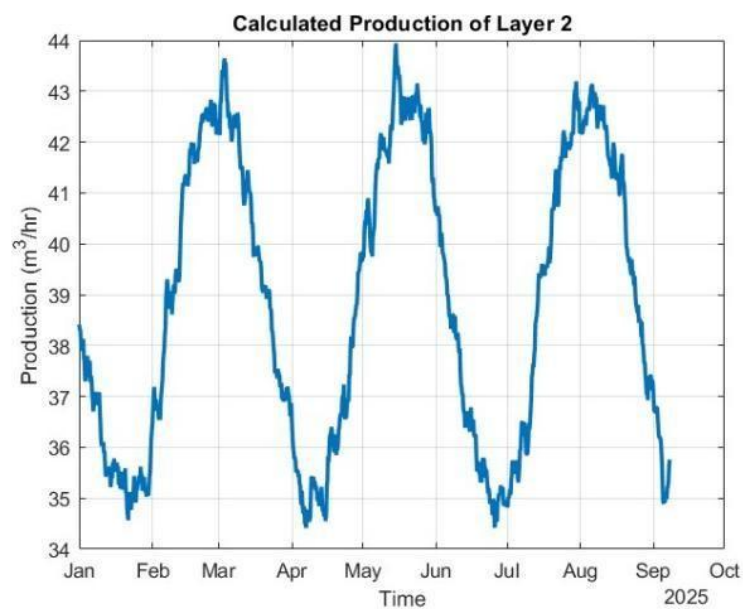


Figure 5.2 Calculated Production of Layer 2

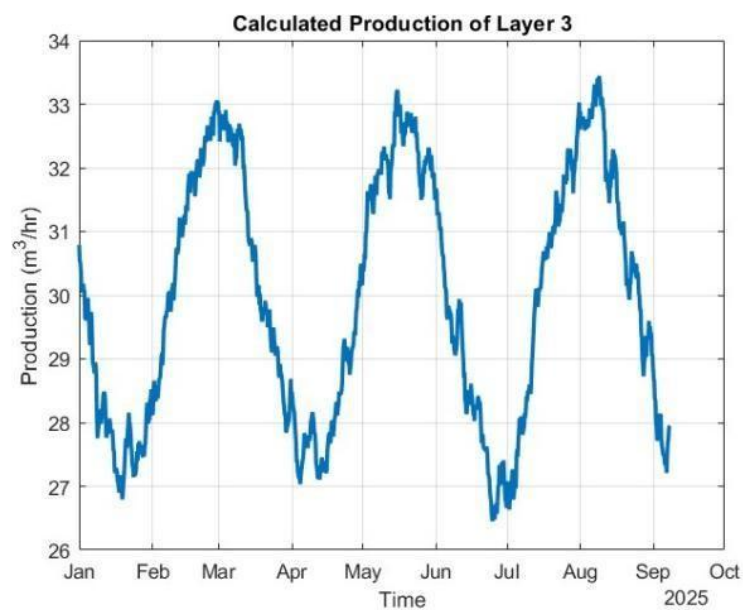


Figure 5.3 Calculated Production of Layer 3

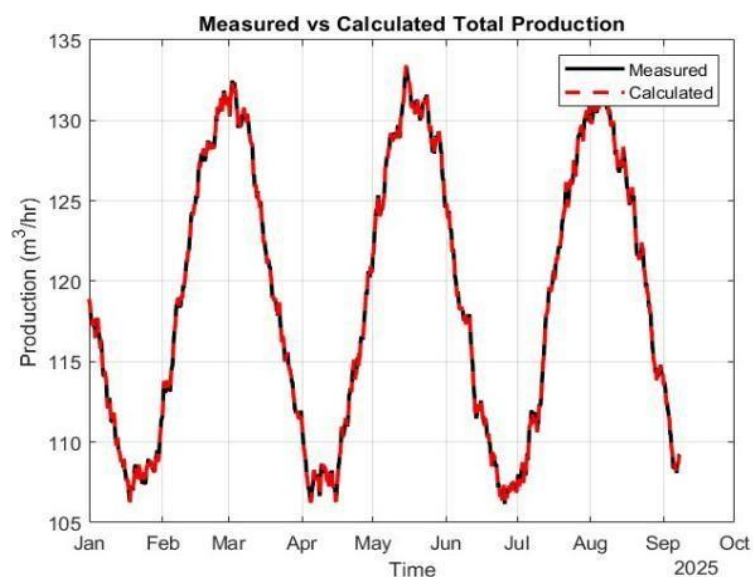


Figure 5.4 Comparison between Measured and Calculated Total Production

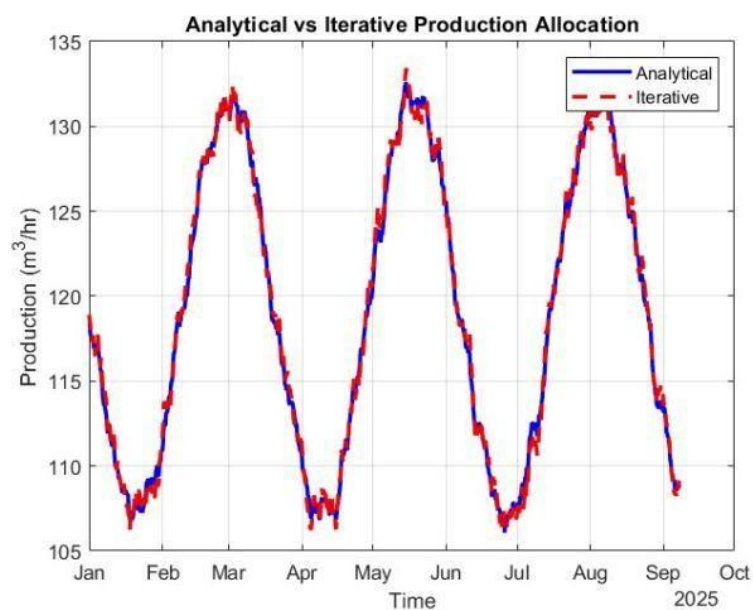


Figure 5.5 Analytical vs Iterative Production Allocation

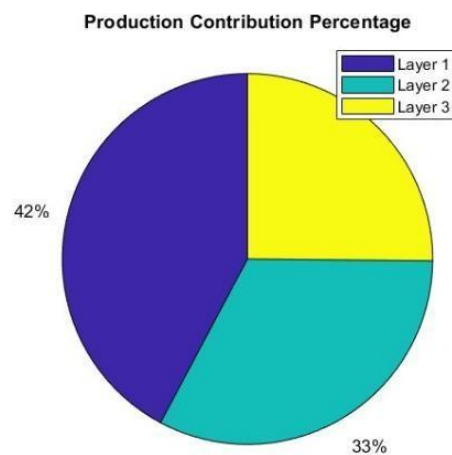


Figure 5.6 Production Contribution of Reservoir Layers

