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Rapid PVT Model Improvement Using Risk Analysis Technique in Gas Condensate Reservoirs

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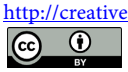


Abstract

A realistic model of reservoir fluid samples is essential before conducting reservoir simulations, especially for gas condensate reservoirs. Errors in PVT modeling typically stem from three main sources: fluid sampling, fluid property measurement, and fluid model construction. This work presents a rapid method for constructing a more realistic PVT fluid model before tuning. Three fluid samples from different Iranian gas condensate reservoirs were selected to achieve this. A suitable equation of state (EOS) and appropriate correlations for key factors like critical pressure, temperature, acentric factor, and binary interaction coefficients were chosen using sensitivity and risk analysis techniques. The optimal default selection of a PVT model produces a representative model of the real fluid sample with minimal variation in variables when matching laboratory data. This approach is applicable to various PVT modeling packages. Before model optimization, a base model is selected based on literature and experience. The sensitivity and risk analysis technique uses the residual mean square (RMS) error as the objective function. The results of this work indicate that a significant number of models constructed using the derivative method had lower RMS errors compared to the base model. The risk analysis technique is shown to provide the best default selection for the PVT fluid model. While some approaches in the literature recommend using specific EOS and correlations for gas condensate samples, the results of this work show that the interaction effect of PVT model variables leads to the best combination of EOS and correlations for each PVT sample. This approach can be extended to improve the PVT modeling process.

Subject Areas

Chemical Engineering & Technology, Petroleum Geology

Keywords

Gas Condensate Reservoir, Fluid Model, Risk Analysis, PVT Model, Residual Mean Square

1. Introduction

Gas condensate field development planning requires compositional simulation studies to appraise gas and condensate reserves, production methods, and surface facilities design [1] [2]. Determining PVT properties is crucial for all reservoirs but plays an especially vital role in gas-condensate reservoirs. For instance, condensate/gas ratio plays a major role in estimates for the sales potential of both gas and liquid. In fact, it is central to our understanding of gas condensate reservoirs. EOS-based fluid modeling involves several critical steps, including optimal component selection by means of C_{7+} characterization, incorporating robust phase equilibrium calculations and solution techniques to ensure convergence, and a rigorous regression method to tune the model to laboratory data [3] [4]. Incorrect default PVT model suggestions prior to tuning, the last step can be time-consuming and often frustrating. The tuning or regression of the EOS parameters should be performed if the EOS model does not match fluid properties from experimental data. Tuning requires trial and error in setting regression parameters and data weight factors [5]. To construct a tuned model, various PVT software products have been developed [6]. Choosing default equations and correlations before tuning is the common step of all software packages. Afterward, automatic or manual adjustments of EOS parameters can be performed [7].

The choice of which model to use as a default before manual or automatic tuning depends on fluid type and condition. Research to date has focused on suggesting correlations for special conditions rather than offering a unique method. Some approaches recommend using specific EOS and the correlations for gas condensate samples. For example, the Modified Redlich-Kwong-Soave may be better for fluids such as black, low and medium volatility oils and lean gases far from the critical point. The Peng-Robinson EOS is preferred for highly volatile oils or liquid-rich gas condensates nearer the critical point. It may be necessary to use more than one model. For instance, the Modified Redlich-Kwong-Soave EOS generally gives poor density predictions. Sometimes, the Benedict-Webb-Rubin-Starling equation is used to calculate densities [8]. These findings might have been much more convincing if they resulted from a unique approach.

Recent software developments in PVT have heightened the need for a unique method to initialize model tuning. In this paper, we propose a much more systematic approach to identify the best equation of state (EOS) and correlations for constructing an appropriate representative model (default model) with minimal variable variation, ultimately improving the process of tuning to laboratory data. The primary purpose of this research is to enhance the accuracy and efficiency of

PVT modeling by optimizing parameter selection and providing a clear framework for model initialization, thereby facilitating better predictions and insights into reservoir behavior.

2. Problem Definition

The main objective of this paper is to determine the best default selection of PVT fluid model before utilization of tuning process (Figures 1 (a)-(c)). Generally, to match the observed data, two steps should be taken. First, robust equations and correlations are selected as a default (physical part). Most of the existing software packages offer unique correlations for any kind of PVT data. Second, based on suggested equations, the tuning process is conducted. As shown in Figure 1(c), using an improper default model leads to a severe and time-consuming tuning process.

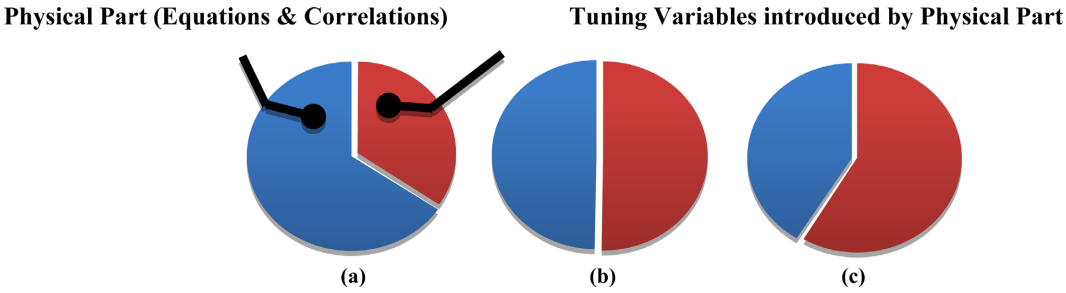


Figure 1. Relative contribution of default model selection process (blue) and regression (orange) process to match observed data.

Throughout the life of a hydrocarbon reservoir, from discovery to abandonment, a great number of decisions depend on incomplete and uncertain information [9]. The novelty of the study is choosing the best default composed of correlations for different PVT parameters based on PVT samples to mitigate uncertainty. Then, PVT equation of state, critical properties, acentric factor and binary interaction coefficients are introduced as uncertain parameters to construct default PVT model considering PVT sample. Combination of all PVT correlations to select the best PVT default is not reasonable due to vast run and consequently, it is a time-consuming process. So, it is necessary to propose a novel workflow in which the PVT default will be chosen rapidly by minimum run for each PVT sample.

3. Proposed Workflow

PVT modeling of conventional default (software suggestion) is performed as a base run. Next, sensitivity analysis to distinguish the most effective parameters on residual mean square (RMS) is implemented. The sensitivities are then used to modify the unknown model parameters to correlate the predicted data. On completion of PVT correlation combination step, the process of default model specification and parameter estimation was carried out. The workflow was tested in three PVT models of gas condensate. Proposed workflow is shown in Figure 2.

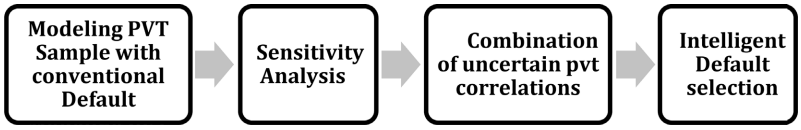


Figure 2. Proposed algorithm for determination of default PVT model before tuning.

3.1. Conventional Default PVT Modeling

All the available software packages offer default equations and parameters based on literature and developer's viewpoints. As mentioned before, some approaches in literature recommend using specific EOS and correlations for specified fluid type. Although these suggestions may be appropriate in some cases, it is not possible to consider them as a general rule.

3.2. Sensitivity Analysis

Sensitivity analyses are performed to evaluate the gradients of the error functions with respect to the model parameters used in the analysis. It quantifies the uncertainty in a model's estimates by analyzing variations in the model's parameters. Thus, sensitivity analyses can be used to reduce time of analysis. Efficient parameter selection is crucial for reducing computational costs while ensuring accurate results because it minimizes the dimensionality of the model, enhances the convergence of numerical algorithms, and optimizes resource usage. By focusing on the most influential parameters through sensitivity analysis, we can streamline computations and improve model performance.

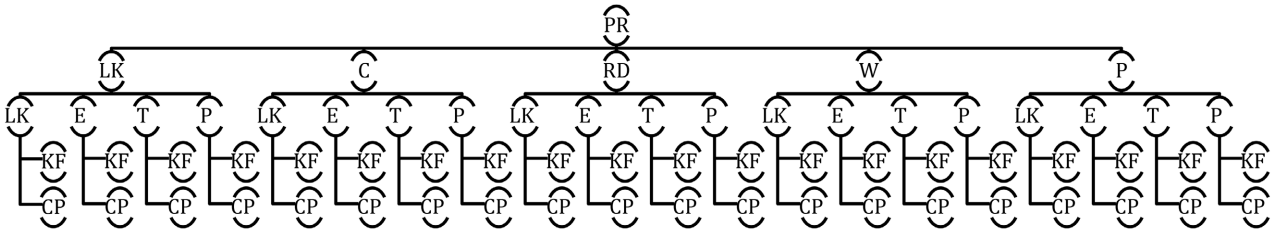
3.3. Risk Analysis

Petroleum industry is a classic case of decision-making under uncertainty; it provides an ideal setting for the investigation of risk corporate behavior and its effects on the firm's performance [10]. The decision tree analysis technique for making decisions in the presence of uncertainty can be applied to many different project management situations. A decision tree is a decision support tool used in operational research. It helps with decision-making regarding strategies and managing conditional probabilities. Decision trees are a part of the decision theory approach widely used by decision makers while dealing with few possible solutions. Decision trees are diagrams that can be used to represent decision problems so that their structure is made clearer.

Figure 3 shows a decision tree to calculate RMS for Peng Robinson EOS. Unlike decision tables, decision trees can represent problems with sequential decision-making, where decisions must be made at different stages in the problem. Decision trees constitute a potent and important tool for modeling and optimization of probabilistic multistage decision-making problems.

4. Result

The proposed workflow was applied to three gas condensate PVT models. Table 1 compares the composition of three Iranian gas condensates. After implementation



EOS	Crit. Prop.	Acentric Prop.	BIC
Peng Robinson (PR)	*Lee-Kesler (LK)*	*Lee kesler (LK)*	*Katz and Firouzabadi (KF)*
Soave-Redlich-Kwong (SRK)	*Cavett (C)*	*Edmister (E)*	*Cheuh and Prantsits (CP)*
Redlich–Kwong (RK)	*Riazi doabert (RD)*	*Thomassen (T)*	
Zudkevitck-Joffe (ZJ)	*Winn (W)*	*Pedersen(P)*	
3 Parameter Peng Robinson (PR3)	*Pedersen (P)*		
3 Parameter Soave-Redlich-Kwong (SRK3)			
Schmidt-Wenzel (SW)			

Figure 3. Decision tree for calculation of RMS for Peng Robinson equation of state.

Table 1. Compositions of three Iranian gas condensate samples.

Sample one	
Component	Mole Fraction
H_2S	0.0394
N_2	0.1086
CO_2	0.0238
C_1	0.6643
C_2	0.0650
C_3	0.0281
IC_4	0.0052
NC_4	0.0103
IC_5	0.0032
NC_5	0.0034
C_6	0.0057
C_7	0.0086
C_8	0.0090
C_9	0.0068
C_{10}	0.0045
C_{11}	0.0020
C_{12+}	0.0121
Sample two	
Component	Mole Fraction
N_2	0.02104
CO_2	0.00179

Continued

C_1	0.82174
C_2	0.06308
C_3	0.03438
IC_4	0.00536
NC_4	0.01309
IC_5	0.00439
NC_5	0.00454
C_6	0.00587
C_7	0.00461
C_8	0.00399
C_9	0.00350
C_{10}	0.00240
C_{11}	0.00212
C_{12}	0.00137
C_{13}	0.00127
C_{14}	0.00103
C_{15}	0.00087
C_{16+}	0.00356
Sample three	
Component	Mole Fraction
CO_2	0.0217
N_2	0.0034
H_2S	0.0000
C_1	0.7064
C_2	0.1076
C_3	0.0494
NC_4	0.0302
NC_5	0.0135
C_6	0.0090
C_{7+}	0.0588

of sensitivity analysis and combination of uncertain parameters for each sample, the best default correlation was selected. In the following, the results of three samples are explained.

4.1. Fluid Sample One

Table 2 shows the results obtained from the sensitivity analysis. As it can be seen,

change of EOS has the most effect on RMS for this sample. Figure 4 is used to determine the most effective parameter for Sample 1. ZJ, RK and PR3 EOS, Crit. Prop.-RD, Crit. Pro.-RD and C, Acentric Prop.-T and E have the minimum RMS in their category.

Table 2. Sensitivity analysis of Sample one.

Sample one						
	EOS	Critical Properties	Acentric Factor	BIC	RMS	Rang Variation
Default	PR3	LK	LK	KF	0.485260422	0
EOS-PR	PR	LK	LK	KF	0.534117582	
EOS-SRK	SRK	LK	LK	KF	0.697698914	
EOS-RK	RK	LK	LK	KF	0.524950261	0.212438491
EOS-ZJ	ZJ	LK	LK	KF	0.366278359	
EOS-SRK3	SRK3	LK	LK	KF	0.619860615	
EOS-SW	SW	LK	LK	KF	0.490236014	
Crit. Pro.-C	PR3	C	LK	KF	0.434776005	
Crit. Prop.-RD	PR3	RD	LK	KF	0.389446076	0.04532993
Crit. Prop.-W	PR3	W	LK	KF	0.492002072	
Crit. Prop.-P	PR3	P	LK	KF	0.539034893	
Acentric Prop.-E	PR3	LK	E	KF	0.442734145	
Acentric Prop.-T	PR3	LK	T	KF	0.410902436	0.03183171
Acentric Prop.-P	PR3	LK	P	KF	0.673873215	
BIC-CP	PR3	LK	LK	CP	0.437909819	−0.04735060

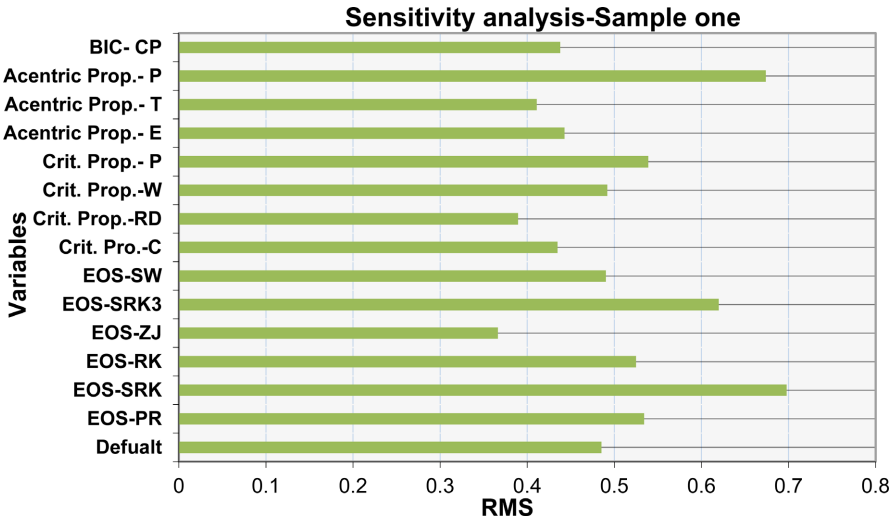


Figure 4. Determination of sensitive parameters for Sample one.

Three EOS and two other correlations (Critical Properties, Acentric Factor, and BIC) were selected for the rapid construction of the PVT model, respectively (Table 3).

24 runs (combination of **effective** parameters) were done and the best model with minimum RMS was selected as a default model. To verify the method, all 280 ($7 \times 5 \times 4 \times 2$) runs were also performed.

Figure 5 depicts the cumulative distribution function for Sample 1. Since the vertical axis is probability, it must fall between zero and one. It increases from zero to one as we go from left to right on the horizontal axis. Intuitively, it is the "area so far" function of the probability distribution.

Table 3. Selection of effective correlation for Sample one.

Correlation	Parameter 1	Parameter 2	Parameter 3
EOS	ZJ	PR3	RK
Critical Properties	RD	C	-
Acentric Factor	T	E	-
BIC	CP	KF	-

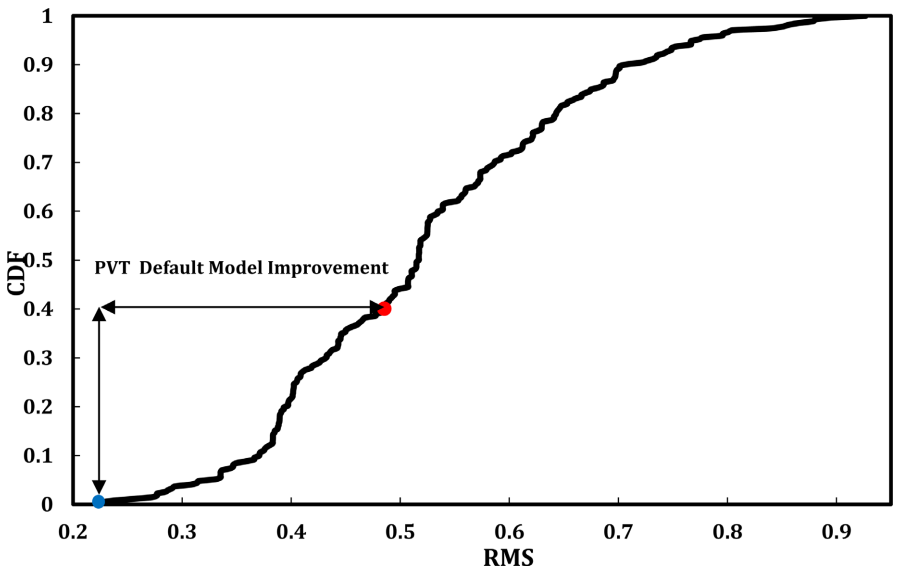


Figure 5. PVT default model position compared with other PVT models (Sample one).

Position of conventional default (red point) is shown in Figure 5. Applying the proposed workflow and using effective parameters (Table 3) decreases the default model RMS significantly (blue point).

All models existing between these two points are constructed by correlations and parameters, which were picked out from sensitivity analysis. Using sensitivity analysis, the optimal model before conducting tuning was achieved quickly.

4.2. Fluid Sample Two

Table 4 shows RMS and its variation range as a result of sensitivity analysis. For

Sample 2, PR3, SW EOS, Critical Prop-RD and W, C, Acentric Prop.-E and T have minimum RMS in their category. Three and two effective EOS, and other correlations (Critical Properties, Acentric Factor and BIC) were selected to rapid construction of PVT model, respectively (see Table 5 and Figure 6).

24 runs (combination of effective parameters) were done and the best model with

Table 4. Sensitivity analysis of Sample 2.

Sample two						
	EOS	Critical Properties	Acentric Factor	BIC	RMS	Rang Variation
Default	PR3	LK	LK	KF	0.245514451	0
EOS-PR	PR	LK	LK	KF	0.247671454	0.032740995
EOS-SRK	SRK	LK	LK	KF	0.278255446	
EOS-RK	RK	LK	LK	KF	0.570884529	
EOS-ZJ	ZJ	LK	LK	KF	0.431359348	
EOS-SRK3	SRK3	LK	LK	KF	0.257132594	
EOS-SW	SW	LK	LK	KF	0.24633074	
Crit. Pro.-C	PR3	C	LK	KF	0.28813747	0.036101523
Crit. Prop.-RD	PR3	RD	LK	KF	0.252035947	
Crit. Prop.-W	PR3	W	LK	KF	0.217270362	
Crit. Prop.-P	PR3	P	LK	KF	1.008775396	
Acentric Prop.-E	PR3	LK	E	KF	0.271869996	0.026355544
Acentric Prop.-T	PR3	LK	T	KF	0.245514452	
Acentric Prop.-P	PR3	LK	P	KF	6.162041322	
BIC-CP	PR3	LK	LK	CP	0.240113473	−0.00540097

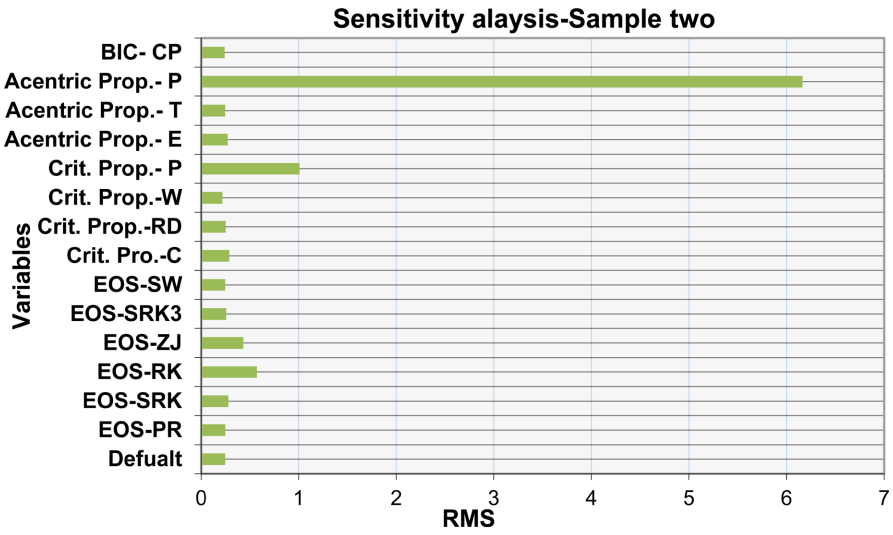


Figure 6. Determination of sensitive parameters for Sample two.

Table 5. Selection of effective correlation for Sample two.

Correlation	Parameter 1	Parameter 2	Parameter 3
EOS	PR3	SW	PR
Critical Properties	RD	W	-
Acentric Factor	E	T	-
BIC	CP	KF	-

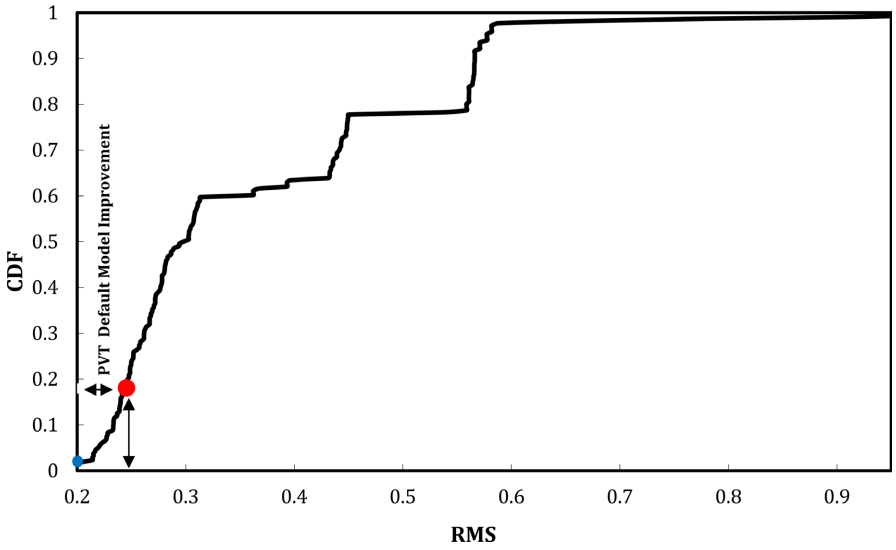


Figure 7. PVT default model position compared with other PVT models (Sample two).

minimum RMS was selected as a default model. In order to compare the result of sensitivity analysis, all 280 (7 × 5 × 4 × 2) runs were performed (see Figure 7).

For this sample, applying the proposed workflow and using effective parameters (Table 4) decreases default RMS. Similar to Sample 1, all models existing between these two points are constructed by correlations and parameters, which are picked out from sensitivity analysis for Sample 2.

4.3. Fluid Sample Three

Table 6 shows RMS and its variation range as a result of sensitivity analysis. SW and PR EOS, Critical Prop.-C and KL, Acentric Prop.-T and E have the minimum RMS in their category. Three and two effective EOS, and other correlations (Critical Properties, Acentric Factor and BIC) were selected to rapid construction of PVT model (Table 7).

24 runs (combination of effective parameters) were done and the best model with minimum RMS was selected as a default model. In order to compare the result of sensitivity analysis, all 280 (7 × 5 × 4 × 2) runs were performed (see Figure 8 and Figure 9).

Using effective parameters decreases default RMS significantly (Table 6). Similar to previous samples, all models existing between these two points are constructed

Table 6. Sensitivity analysis of Sample three.

Sample three						
	EOS	Critical Properties	Acentric Factor	BIC	RMS	Rang Variation
Default	PR3	LK	LK	KF	0.258440063	0
EOS-PR	PR	LK	LK	KF	0.169953169	−0.0222629
EOS-SRK	SRK	LK	LK	KF	0.236177159	
EOS-RK	RK	LK	LK	KF	0.47925448	
EOS-ZJ	ZJ	LK	LK	KF	0.400339469	
EOS-SRK3	SRK3	LK	LK	KF	0.212809663	
EOS-SW	SW	LK	LK	KF	0.160523622	
Crit. Pro.-C	PR3	C	LK	KF	0.203013414	0.071120675
Crit. Prop.-RD	PR3	RD	LK	KF	0.28154613	
Crit. Prop.-W	PR3	W	LK	KF	0.260023063	
Crit. Prop.-P	PR3	P	LK	KF	0.274134089	
Acentric Prop.-E	PR3	LK	E	KF	0.269581614	0.133589516
Acentric Prop.-T	PR3	LK	T	KF	0.272864826	
Acentric Prop.-P	PR3	LK	P	KF	0.40317113	
BIC-CP	PR3	LK	LK	CP	0.163876217	−0.09456385

Table 7. Selection of effective correlation for Sample three

Correlation	Parameter 1	Parameter 2	Parameter 3
EOS	SW	PR	SRK3
Critical Properties	C	KL	-
Acentric Factor	T	E	-
BIC	CP	KF	-

by correlations and parameters which were picked out from sensitivity analysis.

The results from the three gas condensate reservoirs confirm that applying the proposed methodology can significantly reduce the number of simulation runs—by more than 10 times.

5. Discussion

The results of the sensitivity analysis indicate that the equations of state (EOS) have a significant impact on the accuracy of PVT modeling for gas condensates. Sample one showed that the PR3 and ZJ EOS provided lower RMS values, indicating better performance. This highlights the importance of selecting the

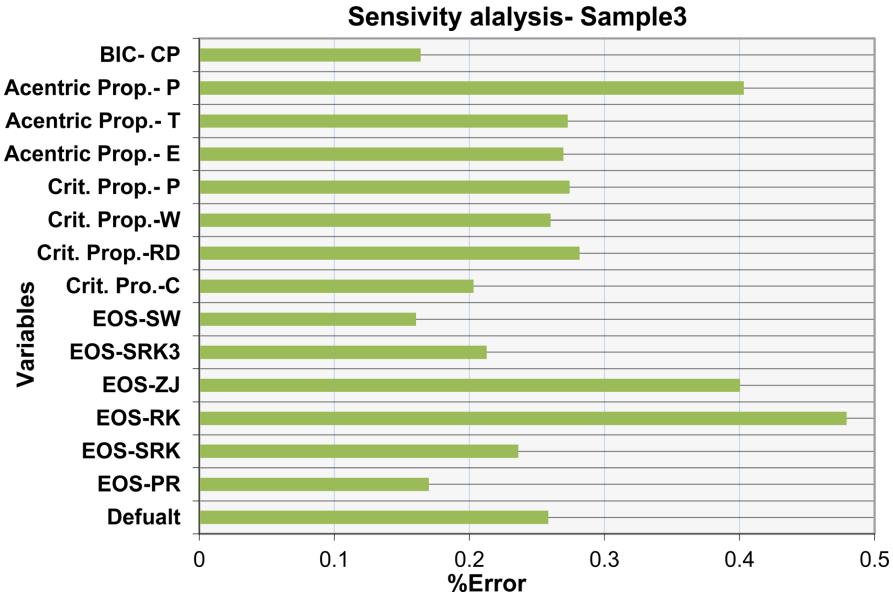


Figure 8. Determination of sensitive parameters for Sample three.

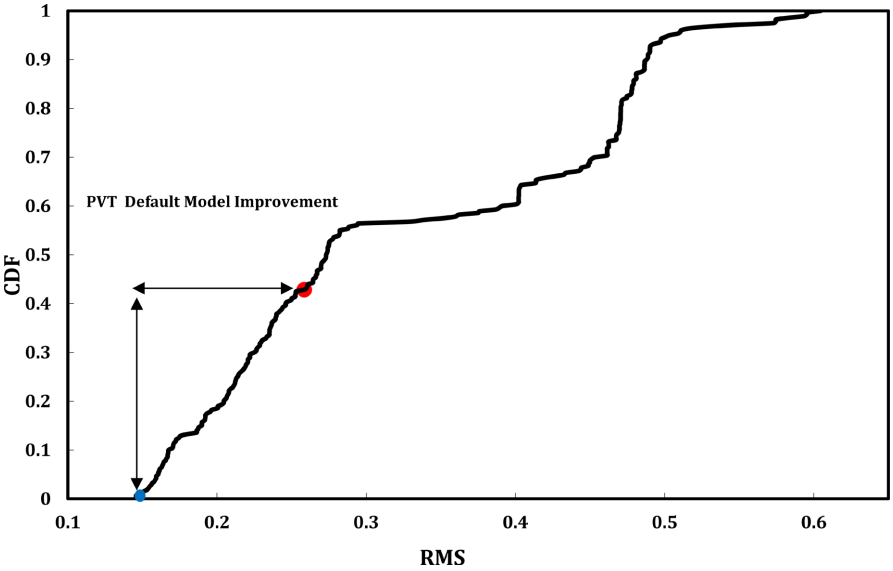


Figure 9. PVT default model position compared with other PVT models (Sample three).

appropriate EOS based on the fluid's characteristics.

In Sample two, the PR3 and SW EOS also performed well, confirming the trend observed in Sample one. The significant variation in RMS values based on critical properties and acentric factors suggests that these parameters should be carefully selected to enhance model accuracy.

Sample three's results reaffirm the necessity of a systematic approach to sensitivity analysis, with the SW EOS providing the best fit. The combination of effective parameters identified through this analysis can lead to more reliable PVT models, reducing the need for extensive simulation runs.

Overall, the proposed workflow demonstrates a robust methodology for rapid PVT model construction. The significant reduction in RMS across samples illustrates

its effectiveness in optimizing gas condensate modeling.

6. Conclusions

This study developed and implemented a novel workflow to efficiently select the best default PVT model before tuning, addressing the challenges posed by high-resolution compositional models. In cases where large numbers of components, such as detailed hydrocarbon fractions or non-hydrocarbon gases, need to be modeled, the computational cost can become prohibitive. Instead of using all available PVT correlations, which would require extensive computational resources, the proposed method significantly reduces the number of runs by focusing on the most relevant parameters for each PVT sample.

By applying sensitivity and risk analysis techniques, the workflow identifies the optimal default model with minimal computational effort, even when dealing with complex, multi-component fluid compositions. The results demonstrate that this approach reduces the number of simulation runs by a factor of 10 while maintaining accuracy in model selection. Furthermore, the analysis reveals that relying solely on generic correlations from existing literature can lead to improper default model choices, particularly in cases of high-resolution compositions. This highlights the necessity of adapted workflows for accurate PVT model selection.

Beyond PVT modeling, this methodology can be extended to other areas, such as reservoir simulation models, well modeling, and production forecasting, where efficient parameter selection is critical to reducing computational costs while ensuring accurate results. The approach offers a practical solution for streamlining the modeling process in various aspects of reservoir engineering, particularly in complex and time-consuming scenarios.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Yang, Y., Lun, Z., Wang, R., Cui, M. and Hu, W. (2024) A New Model Simulating the Development of Gas Condensate Reservoirs. *Energy Geoscience*, **5**, Article ID: 100149. https://doi.org/10.1016/j.engeos.2022.100149

[2] Shelepov, K., Struchkov, I., Poltoranin, V., Trusova, A., Chashchin, M., Kuzevanov, M., *et al.* (2018) Reservoir Development Aspects and Surface Facilities Design of Gas Condensate Fields with Oil Rims (Russian). *SPE Russian Petroleum Technology Conference*, Moscow, 15-17 October 2018. https://doi.org/10.2118/191572-18RPTC-MS

[3] Nagarajan, N.R., Honarpour, M.M. and Sampath, K. (2007) Reservoir-Fluid Sampling and Characterization—Key to Efficient Reservoir Management. *Journal of Petroleum Technology*, **59**, 80-91. https://doi.org/10.2118/103501-jpt

[4] Kamari, A., Mohammadi, A.H. and Ramjugernath, D. (2019) Characterization of C_{7+} Fraction Properties of Crude Oils and Gas-Condensates Using Data Driven Models. *Petroleum Science and Technology*, **37**, 1516-1522.

https://doi.org/10.1080/10916466.2019.1570254

[5] Suwono, S.B., Hendraningrat, L., Febrianto, D.H., Nugroho, B. and Marhaendrajana, T. (2012) Multiple EOS Fluid Characterization for Modeling Gas Condensate Reservoir with Different Hydrodynamic System: A Case Study of Senoro Field. *North Africa Technical Conference and Exhibition*, Cairo, 20-22 February 2012. https://doi.org/10.2118/150822-ms

[6] Schebetov, A., Rimoldi, A. and Piana, M. (2010) Quality Check of Gas-Condensate PVT Studies and EOS Modelling under Input Data Uncertainty (Russian). *SPE Russian Oil and Gas Conference and Exhibition*, Moscow, 26-28 October 2010.

[7] Whitson, C.H., Fevang, Ø. and Yang, T. (1999) Gas Condensate PVT—What's Really Important and Why? *IBC Conference-Optimisation of Gas Condensate Fields*, London, 28-29 January 1999.

[8] Fontaine, T. (1998) Four Reasons Why Your Gas Condensate Fluid Model Is Probably Wrong. Fekete Australia Pty. Ltd.

[9] Corre, B., Thore, P., Feraudy, V. and Vincent, G. (2000). Integrated Uncertainty Assessment for Project Evaluation and Risk Analysis. *Proceedings of SPE European Petroleum Conference*, Paris, October 2000, SPE-65205-MS. https://doi.org/10.2523/65205-ms

[10] Suslick, S.B. and Schiozer, D.J. (2004) Risk Analysis Applied to Petroleum Exploration and Production: An Overview. *Journal of Petroleum Science and Engineering*, **44**, 1-9. https://doi.org/10.1016/j.petrol.2004.02.001