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PVT Modeling of Qaiyarah Oil Field

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ABSTRACT

Qaiyarah oil field is characterized by its complexity due to its extra heavy oil reaching 16° API. Thus, building a systematic PVT model for this field at a specific range of temperatures is a powerful challenge for screening such reservoirs. The peng-Robenson equation of state model with up to six pseudo components was developed for the crude sample of the Qaiyarah oil field. This work represents the fingerprint for constructing a dynamic model for the field under study. The model also applies to the heavy oil reservoirs under splitting and lumping scenarios. This work suggests a lumping scheme to enhance the accuracy and CPU performance of compositional reservoir simulations. Therefore, the full components model (13 components) is lumped into a reduced number of pseudo components (6 components) to be utilized in the compositional fluid simulation. This study outlines the Peng-Robinson equation of state (EOS) to tune the data at a certain pressure range up to 400 psi. More specifically, various essential parameters have been trained to match the model results with the experimental data. Splitting processes of C6+ into four pseudo components, namely, $HYP0_1$, $HYP0_2$, $HYP0_3$, and $HYP0_4$ is added to the matching picture. Separately, justifying the critical properties introduced a better result of regression. The results showed an acceptable match for Bo with an error percent below 1%, while calculated oil viscosity deviated from measured values in different ranges against pressure variation.

Keywords: Bubble point pressure, Equation of state, Heavy oil reservoirs, Lumping, PVT modeling.

1. INTRODUCTION

Developing a PVT model has been a significant concept to optimize field development and identify a management plan for EOR schemes. Separately, PVT modeling for heavy oil reservoirs has recently gained a huge potential due to its complexity. The modeling involves light to extra heavy components., globally, numerical simulation of such components is performed in compositional modeling to represent the compositional changes. Characterization of heavy oil composition in terms of pseudo components is a vital challenge in PVT modeling. Accurate prediction of PVT characterization for heavy oil reservoirs has

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been a potential candidate for implementing injection-production parameters and dynamic system analysis of multi-thermal fluid stimulation.

Modeling hydrocarbon reservoir performance using EOS fluid characterization and factoring in fluid composition variation shows a potential impact on hydrocarbon recovery **(Ali et al., 2019; Farkha et al., 2023; Alali and Verlaan, 2023)**. Examples are steam injection or in-situ combustion, where the mass transfer occurs between the injected steam and the in-situ hydrocarbons, resulting in the development of the injected fluid into a fluid that is miscible with in-situ hydrocarbons. The PVT model was built based mainly on a massive input data set, including gas oil ratio, molecular weight, relative volume, differential liberation data, and mole fraction for all components up to C6+ components.

To achieve more applicable results, several correlations, including algorithms and neural network models, are introduced to predict oil PVT properties. For example, **(Ahmedzeki et al., 2012; Ali and Naife, 2021)** presented an artificial neural network model to predict the bubble point pressure for Iraqi oil fields. The comprehensive databank collected from certain Iraqi oil reservoirs included reservoir temperature, solution gas-oil ratio, and gas density. At the same time, in the surrounding area, **(Riyahin et al., 2014)** presented an accomplished set of correlations to estimate the properties of Iranian crude oils based on the experimental data. The correlations are applied for oils ranging from 15° to 30° API. Therefore, they introduced a developed correlation to estimate formation volume factor (Bo), solution gas-oil ratio (Rs), and bubble point pressure. Although these correlations have a particular scope, they are all regression approaches of specific crude samples and, consequently, are difficult to apply to other systems. Separately, splitting the heavy components is a key characterization of EOS, and there are several approaches for splitting schemes through PVT modeling. Finally, the Whitson method was selected. Several studies have been proposed based on splitting schemes. To generate a compositional reservoir fluid modeling, dealing with many full components demands a huge computer storage. This issue is solved by suggesting lumping/grouping the detailed components into a set of pseudo components. Several approaches have been proposed in the literature, including lumping fractions **(Michelsen, 1982)**.

Building a PVT model for a multi-component fluid system obtained from fluid analysis results required performing a regression for key laboratory tests such as constant mass expansion, differential liberation results, and oil viscosity **(Asaee et al., 2014; Al-Waeli et al., 2017; Nabipour and Baghban, 2019; Kerr et al., 2020)**. Characterization of multiphase flow (oil, water, and gas) has been a crucial issue. Therefore, **(Liu et al., 2021; Quinones-Cisneros et al., 2004; Fouad et al., 2018)** developed a thermal simulator applicable to multiphase flow and regressed it with the commercial simulators to achieve wide applicability at various thermal conditions .

Limited phase behavior studies of extra-heavy oils have been available in the literature. **(Ghasemi and Whitson, 2021)** developed an approach to model the volumetric behavior of heavy oil for an extended range of temperatures using a modified Jacoby correlation.

The present study aims to provide insight into heavy oil modeling and its sensibility toward crucial parameters by an acceptable agreement between experimental data related to the EOS outputs. Consequently, it can predict the properties of the PVT model for the heavy oil of the selected field. The PVT model built for the Qaiyarah oil field would be utilized as a fingerprint in dynamic modeling for the field under study.

2. BRIEF DESCRIPTION OF QAIYARAH OIL FIELD

Qaiyarah oil field is located 50 km south-east of Mousil city in northern Iraq. The field was initially discovered by well QY-1 in 1928. The structure corresponds to a narrow, long anticline with orientation from northwest to southeast, characterized by a flank dip of 6 to 10 degrees **(Al-Jaff and Hamd-Allah, 2023)**. The Jeribe and Euphrates formations, separated by a thin Dhiban formation, are the main pay formations of the reservoir. Initial reservoir pressure was estimated at a depth of 50 m subsea level to be 400 psi with an average reservoir pressure gradient of 0.401 psi/ft recorded at the oil zone and 0.433 psi/ft in the water zone. **Fig. 1** shows the location of Qaiyarah oil field on the map.

Figure 1. Location of Qaiyarah oil field.

3. METHODOLOGY OF PVT CHARACTERIZATION

The PVT modeling requires PVT laboratory data, including differential liberation data (Gas-oil ratio, gas deviation factor, oil formation volume factor, oil viscosity, and oil specific gravity), constant composition expansion data and heavy components characteristics including mole fractions, density and molecular weight of C6+ **Table 1**.

Table 1. Oil composition at initial conditions

Component	Composition (Mole fraction)	Component	Composition (Mole fraction)
H_2S	0.009	IC_4	0.0212
CO_2	0.0035	NC_4	0.045
C_1	0.0443	IC_5	0.0389
C_2	0.1908	NC_5	0.04
C_3	0.0576	C_6^+	0.5897
Sum of the mole fraction is 1			

Modeling heavy oil properties constitutes a potential challenge and vital input data for reservoir modeling. The heavy oil modeling in terms of pseudo- components is another problematic conflict due to the economic restriction related to the number of pseudo-components.

An essential requirement for building the PVT model is the saturation pressure at 110 °F is 265 psi, oil formation volume factor at bubble point equals to 1.061, and initial GOR is 115 ft^3/bbl. The main composition of the sample under study is given in **Table 1**.

3.1 Splitting Processes

Splitting is the process of breaking down plus fractions into pseudo components characterized by mole fractions to achieve the applicability of the equation of state.

In this study, Two Stages-Exponential splitting was used to redistribute the molar fraction. Various attempts were made to get a match for all key parameters by characterizing EOS, resulting in failed matching. Separately, splitting and lumping processes have been utilized for tuning EOS to regenerate PVT experiments. The multi-step process was started by splitting the heavy components as presented by Whitson using two stages- exponential for characterization of the molar distribution and petroleum fraction physical properties, consequently enhancing EOS prediction accuracy.

After several splitting scenarios for a heavy component C6+, it was indicated that the splitting into four pseudo components showed a candidate match. The pseudo components had been identified as HYP01, HYP02, HYP03, and HYP04. **Table 2** shows the new components after the splitting scenario. After splitting, the total number of components increased from 10 to 13.

Table 2. Pseudo components properties.

Component	Composition (%)	Pc (atm)	Tc (^oK)	Mw (lbmol/lbm)	μ (cp)	SG
H_2S	0.009	88.2	373.2	34.08	0.0985	0.801
CO_2	0.0035	7.8753	1045.4	643.4	1.854	0.985
CH_4	0.0443	72.8	304.2	44.01	0.094	0.818
C_2H_6	0.1908	45.4	190.6	16.043	0.099	0.300
C_3H_8	0.0576	48.2	305.4	30.07	0.148	0.356
IC_4	0.0212	41.9	369.8	44.097	0.203	0.507
NC_4	0.045	36	408.1	58.124	0.263	0.563
IC_5	0.0389	37.5	425.2	58.124	0.255	0.584
NC_5	0.04	33.4	460.4	72.151	0.306	0.625
$HYP0_1$	0.1106556	33.3	469.6	72.151	0.304	0.631
$HYP0_2$	0.1892770	22.83	636.838	141.822	0.5734	0.7786
$HYP0_3$	0.1646309	10.16	874.968	371.9	1.42458	0.8872
$HYP0_4$	0.0851364	6.25	1087.477	823.0754	2.15809	0.98792
	Sum=1					

The new mixture of 13 components was used to tune EOS by regression process to match experimental data. Separately, the first regression was investigated upon the critical pressure of the pseudo components, a centric factor (ω), and binary interaction coefficients (δ), providing an acceptable prediction. **Table. 2** lists the modified components and their EOS parameters.

3.2 Lumping Processes

The following conventional step included grouping the 13-component EOS into reduced pseudo components for compositional modeling to reduce time consumed through reservoir fluid simulation, referring to the lumping process. The Lumping process includes generating new pseudo components from the heaviest components. Then, the properties of the newly generated components were tuned by regression performance. **(Fleming and Wong, 2015; Meziani et al., 2018; Ali et al., 2019; Liu et al., 2020; Izadi and Jafarzadegan, 2021; Samba et al., 2023)** stated that using the lumping technique significantly contributes to CPU time saving through phase-behavior calculations. Accordingly, to build a compositional reservoir model and thermal EOS development, dealing with a large range of components is computationally more expensive and demands large computer storage. Therefore, to solve this issue, it has been recommended to group the components into reduced sets, including pseudo components. Various proposals for lumping processes were considered. The main criterion for the grouping was based on the selection components characterized by similar properties and molecular weight as maintained by **(Rastegar and Jessen, 2009; Elizalde et al., 2009; Chen et al., 2020; Ghorayeb et al., 2022; Soto-Azuara et al., 2022)**.
The 13-components model was reduced under the lumping process to produce six components for the combinations: (H_2S-CO_2), (CH_4-C_2H_6,C_3H), (IC4-NC4), (HYP01-HYP02) and (HYP03-HYP04). **Table 3** presents the generated lumped composition corresponding to the mole fraction. To achieve an optimum regression, the PVT model was rematched by adjusting the critical properties of the grouped pseudo components as stated in the literature **(Maes et al., 2016; Zirrahi et al., 2017a; Zirrahi et al., 2017b; Azinfar et al., 2018a; Azinfar et al., 2018b; Ahmed et al., 2023; Chamgoué et al., 2023; Ratnakar et al., 2017; Hameed et al., 2018; Hadi and Hamd-Allah, 2020). Table 4** summarizes the results of the regression parameters after the lumping process.

Table 3. Components mole fraction after lumping process.

Components	Mole Fraction	Components	Mole Fraction
H_2S to CO_2	0.0125	IC5 to NC5	0.0789
CH_4 to C_3H	0.2927	HYP to HYP	0.29993263
IC4 to NC4	0.0662	HYP to HYP	0.24976737

Gauging the accuracy of the lumping scheme showed that the presented strategy was in good agreement with the observed data. **Figs. 2** to **4** compare the measured oil formation volume factor, oil specific gravity, and oil viscosity, respectively, with the lumped and detailed components after the splitting and regression process.

Table 4. Regression parameters after lumping processes.

components	Pc (atm)	Tc(K)	Acentric factor*10^{-2}	Mol. weight	Vc (mole)$^{-1}$ *10^{-2}	Omega A	Omega B *10^{-2}
H_2S to CO_2	83.838	353.5	13.5	36.86	9.723	0.457	7.780
CH_4 to C_3H	47.097	303.595	9.5	30.707	15.035	0.457	7.780
IC4 to NC4	37.011	419.628	18.756	58.124	2.576	0.457	7.780
IC5 to NC5	33.352	465.045	23.917	72.151	30.499	0.457	7.780
HYP to HYP	12.670	770.306	80.980	274.813	108.778	0.457	7.780
HYP to HYP	4.860	1112.546	155.926	1086	248.316	0.457	7.780

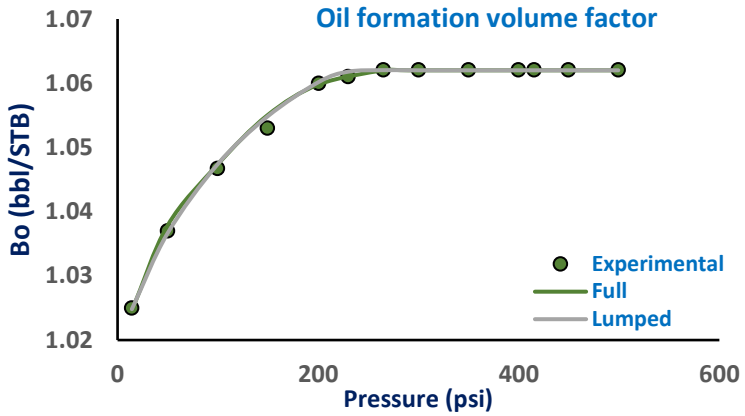

Figure 2. Comparison of measured Bo with the predicted Bo based on lumped and full fluid description.

4. RESULTS AND DISCUSSION

After the regression operation of PR-EOS parameters, the model is arranged for evaluation and performance prediction. To reach the best results, careful justifying of the critical properties and acentric factors was performed. Therefore, after carefully adjusting the EOS parameters, the results showed that the observed data relating to oil formation volume factor, oil viscosity, and oil specific gravity matched the model results more at a pressure above the saturation pressure, as shown in **Figs. 2** to **4**. The performance of the lumping scheme is investigated. The results showed that the investigated lumped scheme can achieve an acceptable prediction of PVT performance.

In this work, we have proposed a splitting and lumping framework referring to the rapprochement of the molecular weight and the composition of the components for reducing the number of detailed descriptions through PVT modeling to be more suitable for fluid simulation. We have started the application of the proposed lumping scheme for a crude sample taken from Jeribe formation characterized by rich experimental data to gauge the certainty of the lumped fluid. It is, however, likely that a regression framework is preferable to be included in the proposed study to maintain the required accuracy if a detailed fluid is lumped into six or fewer pseudo components.

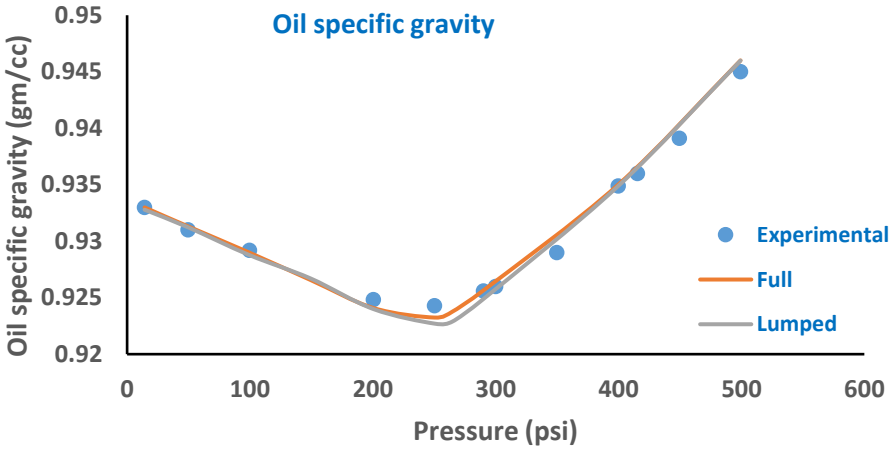

Figure 3. Comparison of measured oil-specific gravity with the predicted based on the lumped and full fluid description.

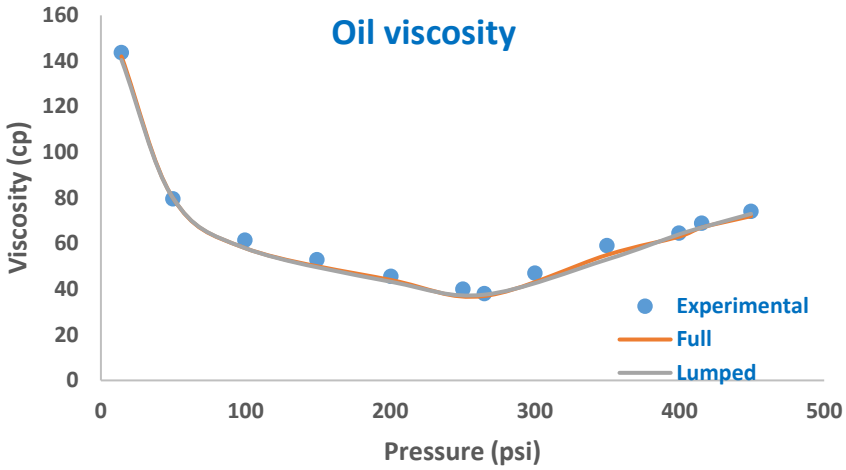

Figure 4. Comparison of measured oil viscosity with the predicted based on lumped and full fluid description.

The earlier matching attempts utilized various types of splitting, including exponential, 2_Stage exponential, and Gamma methods. In this work, 2_Stage exponential showed good compatible results.

Regarding the splitting scheme, several scenarios have been investigated for splitting the heavy component (C6+), including seven, six, and four pseudo components, to achieve an acceptable match between observed and calculated data. Finally, it has been found that splitting into four pseudo components showed a candidate match.

In this study, the detailed EOS model has been used by tuning it properly to the laboratory PVT data to develop a pseudoized EOS model that has a major role in gauging how much the accuracy of a certain lumped EOS model since it is compared directly with the detailed EOS model. It is worthy to prevail that, unfortunately, lumping approaches do not have any background about the generated compositions during EOR processes.

The regression showed a noticeable deviation in comparison of Ping-Robinson EOS to the experimental data below bubble point pressure. As stated above, there was a noticeable deviation in the values due to the gas liberation continuously associated with the gas composition at this stage of pressure decline, as shown in **Fig. 2**. The resulting Bo values ranged from 1.025 to 1.061 bbl/STB based on the range of the observed PVT data. Oil-specific gravity fitted with the measured values introduced a reasonable match. **Fig. 3**, regarding bubble point pressure regression, showed better matching, recording 265 psi corresponding to the specific gravity of 0.924. However, some observed points were not fully regressed. This is a clear signal that the EOS 's parameters were recommended to be adjusted to regenerate the reservoir fluid behavior. The Peng-Robison model was the accurate correlation for oil-specific gravity prediction. A good match had been generalized for Bo and oil-specific gravity with less than 1% deviation. **Fig. 4** shows a relatively acceptable match between experimental oil viscosity and the predicted values. The deviation of the lumped and the full sets was 0.07% below the saturation pressure but only 0.025% when the pressure was above bubble point pressure.

5. CONCLUSIONS

The lumping scheme is investigated to reduce the full fluid description into lumped groups to be more suitable for compositional fluid simulation. This is according to the authors'

knowledge; the first fingerprint includes the compositional modeling of Qaiyarah's heavy oil. Therefore, constructing a PVT model for the Qaiyarah oil field, characterized by its complex composition, is a crucial challenge. This work is successfully tested upon a wide range of temperatures and compositions to predict oil viscosity, oil formation volume factor, and oil specific gravity for the field under study. The data utilized to develop the PVT model were obtained from flash differential liberation in combination with PVT data. It has been concluded that PR-EOS will be maintained for the estimation of the parameters for similar models in the field under study.

We have presented the application of the proposed splitting and lumping schemes of the reservoir fluid with the associated rich set of observed data to gauge the accuracy of the proposed model.

The pseudoized equation of the state model with only six heavy oil pseudo components provided an accurate prediction for a wide range of temperatures. The earlier match between the observed and calculated values was achieved by adjusting the critical properties influencing the PR-EOS results. Lumping the heavy oil components was the key parameter for matching the experimental results with an acceptable fit of the calculated data. The presented results showed that the suggested lumping scheme can achieve a good prediction of PVT data. However, it is recommended that the regression stage is preferred to be included in the proposed scenario as the detailed fluid composition is lumped into six or less pseudo components.

NOMENCLATURE

Symbol	Description	Symbol	Description
Bo	Oil Formation Volume Factor, bbl/stb	RSK	Redlich Kwong Soave
CPU	Central Processing Unit	SG	Specific Gravity
EOS	Equation of State	Tc	Critical Temperature, K
GOR	Gas Oil Ratio, scf/stb	Vc	Critical Volume, 1/mole
Mw	Molecular Weight, lbmole/lbm	μ	Viscosity, cp
Pc	Critical Pressure, atm	δ	Binary Interaction Coefficient
PR	Peng Robinson	ω	Centric Factor
Rs	Solution Gas Oil Ratio, scf/stb		

Credit Authorship Contribution Statement

Layla S. Al-Jaff: Writing – review & editing, Validation, Software, Methodology. Sameera M. Hamd-Allah: Review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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نمذجة الضغط والحجم والحرارة لحقل القيارة النفطي

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الخلاصة

حقل القيارة النفطي نادرا ما يتم وضعه تحت الدراسة وذلك لطبيعته المعقدة ونفوطه الثقيلة جدا بدرجة 16 من مقياس معهد البترول الامريكي. لذا فان نمذجة خواص الموائع لهذا الحقل لمدى معين من درجات الحرارة يعتبر تحدي كبير لتمثيل هذا النوع من المكامن. تمت النمذجة المكمنية اعتمادا على مدخلات بيانية متمثلة بنسبة الغاز الى النفط، الوزن الجزيئي، الحجم النسبي، بيانات التفاضلية الجزئية النسبة المولية لكل المكونات لغاية المكونات الثقيلة بتسلسل 6 واعلى. تم استخدام معادلة بنك روبنسون لتمثيل نموذج نفطي لحقل القيارة النفطي. لذلك تم تقديم هذا الموديل لمطابقة البيانات المقاسة. تمثيل معادلة الحالة تستخدم لتمثيل ادائية المكامن الهيدروكربونية مع التباين في مكونات المائع اظهر تأثير مهم على معدل استخلاص الهيدروكربونات. مثال على ذلك حقن البخار والاحتراق الموقعي حيث يتم تبادل الكتلة بين البخار المحقون والهيدروكربونات المحترقة مما ينتج عن تطويل المائع المحقون الى مائع ممتزج مع الهيدروكربونات المحترقة. في هذا البحث، تم تقديم عملية الاختزال لتحسين دقة و معالجة البيانات لنمذجة الموائع الركيبية لذلك تم اختزال المائع بمكوناته الثلاثة عشر الكاملة الى موديل مختزل مكون من ستة مكونات فقط ليتم استخدامه في نمذجة الموائع المركبة.

عوامل عديدة تم اختبارها للوصول الى التطابق بين نتائج الموديل والقيم المقاسة حقليا. التركيب الكيميائي والفيزيائي للمكونات كانت من ضمن المدخلات الاساسية للموديل. من الجدير بالذكر بان عملية التقسيم للمكونات الثقيلة الى أربع مكونات مختزلة اضافت صورة مكملة للمطابقة. بصورة منفردة، ضبط الخواص الحرجة قدمت أفضل النتائج للمطابقة. النتائج التي تم التوصل اليها وضحت بان الموديل قد توصل الى أفضل مطابقة لبيانات معامل التكوين الحجمي مسجلا نسبة خطأ اقل من 1%. بينما لزوجة النفط المحسوبة سجلت انحراف بمعدل متغير مقابل تغير قيم الضغط.

الكلمات المفتاحية: ضغط الفقاعة، معادلة الحالة، حقول النفط الثقيل، اختزال، نمذجة الضغط والحجم والحرارة.