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Global Component Lumping for EOS Calculations

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Abstract

To reduce CPU time in compositional reservoir simulations, a minimum number of components should be used in the equation of state (EOS) to describe the fluid phase and volumetric behavior. A "detailed" EOS model often contains from 20 to 40 components, with the first 10 components representing pure compounds H_2S, CO_2, N_2, C_1, C_2, C_3, i-C_4, n-C_4, i-C_5, and n-C_5. The remaining components represent a split of the heavier C_{6+} material in single-carbon-number (SCN) fractions such as C_6, C_7, C_8 and C_9, or groups of SCN fractions such as C_{10}-C_{12}, C_{13}-C_{19}, C_{20}-C_{29}, and C_{30+}. Occasionally the light aromatics BTX (benzene, toluene, and xylene isomers) are also kept as separate components for process modeling. Today's typical laboratory compositional analysis provides 50-60 components, including isomers with carbon numbers 6 to 10, SCN fractions out to C_{35} and a residual C_{36+}. This is in contrast to the 11-12 components (through C_{7+}) reported in most commercial laboratory reports pre-1980.

A "pseudoized" EOS model might contain only 6-9 lumped components – e.g. lumping "similar" components such N_2+C_1, i-C_4+n-C_4+i-C_5+n-C_5, and some 3-5 C_{6+} fractions. The selection of which components to lump together is difficult because of the huge number of possible combinations. This paper describes a systematic, automated method[1] to search a vast number of feasible pseudoized EOS models based on an initial, detailed EOS model.

The obvious application of pseudoized EOS models is compositional reservoir simulation, where run time is an important issue and fewer components may be important. The method we present is based on (1) quantifying the "quality of match" between a pseudoized EOS model and the detailed EOS model from which it is derived, and (2) systematically testing all plausible lumping combinations. The method allows for a set of constraints to be imposed on the lumping of components, such as (1) not lumping certain non-hydrocarbons (e.g. CO_2), (2) forcing the first plus fraction to contain a specific carbon-number component (e.g. C_6), and (3) the last component in the original EOS not being lumped with other heavy fractions (e.g. C_{30+}).

The proposed pseudoization procedure is comprehensive, and founded in the ability of an EOS with fewer components to describe a wide range of phase and volumetric properties covering all of the relevant pressure-temperature-composition (*p-T-z*) space expected for a given reservoir development. The litmus test of quality is how well the pseudoized EOS compares with the detailed EOS model from which it is derived, an EOS that accurately describes all key measured laboratory PVT data. The method proposed will find an optimal pseudoized EOS model to describe all PVT data that are relevant to a particular reservoir development – e.g. depletion performance, immiscible and miscible gas injection, compositional variation, and surface processing.

Introduction

EOS-based compositional modeling is used to simulate reservoirs, production flow lines, compressors, and surface processes. Some of these models require large CPU time (hours or days), mainly reservoir models and transient flowline models. Multi-well gathering pipeline systems can also require substantial CPU time, particularly if they are connected upstream to a reservoir simulation model.

Lee et al. (1982) suggest that C_{7+} fractions can be grouped into two pseudo-components according to a characterization factor

[1] The software used is EOS program *PhazeComp* and model automation platform *Pipe-It*.

determined by averaging the tangents of fraction properties molecular weight, specific gravity, and Jacoby factor plotted vs. boiling point. Whitson (1983) suggests a method to estimate the number of C_{7+} fractions, and how they should be grouped.

Coats (1985) gives a thorough discussion of lumping C_{7+} fractions for modeling the vaporization process in gas condensate cycling, and more generally he gives a set of fundamental criteria and methods to calculated the EOS and LBC viscosity parameters of lumped pseudo-components. The Coats lumping methodology is general and allows "partial lumping" of original components into several pseudo-components. Coats gives a quantitative example of lumping – choosing components to lump, the number of pseudo-components used, and the impact on PVT model quality and reservoir simulation modeling of a gas cycling process.

Li, Nghiem and Siu (1984) suggest a method for grouping components of an original fluid description that uses *K*-values from a flash at reservoir temperature and the "average" reservoir operating pressure. The original mixture is divided arbitrarily into "light" components (H_2S, N_2, CO_2, and C_1 through C_6) and "heavy" components (C_{7+}). Different criteria are used to determine the number of light and heavy pseudo-components. Li, *et al.* also suggest the use of phase diagrams and compositional simulation to verify the grouped fluid description.

Schlijper (1986) treats the problem of retrieving detailed compositional information from pseudoized (grouped) components. Behrens and Sandler (1986) suggest a grouping method for C_{7+} fractions based on application of the Gaussian-quadrature method used in continuous thermodynamics. Although a simple exponential distribution is used with only two quadrature points (i.e., the C_{7+} fractions are grouped into two pseudo-components), Whitson et al. (1989) show that the method is general and can be applied to any molar-distribution model and for any number of C_{7+} groups. Still other pseudoization methods have been proposed by Montel and Gouel (1984), Newley and Merril (1991), Danesh, Xu and Todd (1992), Hustad and Dalen (1993) and Liu (2001). Joergensen and Stenby (1995) investigate twelve lumping methods; they found none of these methods give consistently better results.

The EOS model must provide accurate prediction of phase and volumetric behavior of relevant mixtures flowing through a given system being modeled. Properties of density, viscosity, phase volume split, and phase compositions are used in model calculations. Depending on the range of *p-T-z* space, the EOS model required may contain different numbers of components – e.g. nine for reservoir simulation, six for flow assurance, and 22 for process modeling. It is recommended to have a single, detailed EOS model that describes ***all*** PVT data throughout the range of *p-T-z* for the entire petroleum system. The detailed "*EOSxx*" model can have 20-40 components, depending on the software used and company practices in EOS model building.

To obtain a process-specific *pseudoized* "*EOSx*" model (typically with less than 10 components), the relevant *p-T-z* conditions must be well defined for a particular application. The choice of lumped components used in a pseudoized EOS is process dependent – i.e. dependent on the range of pressure, temperature, and composition being modeled.

This paper describes a methodology to find the most appropriate pseudoized *EOSx* model to describe a particular process. The *EOSx* model should represent the detailed *EOSxx* model that has been developed to describe PVT behavior for all relevant *p-T-z* conditions throughout the petroleum production system. The *EOSx* model may describe only the relevant subset of the entire *p-T-z* space particular to the process being modeled – e.g. reservoir processes of depletion and gas injection.

The theoretical number of possible combinations (N_{EOSx}) of $i=1,\ldots,N_{xx}$ components in a detailed *EOSxx* model that are allowed to be pseudoized[2] into an *EOSx* model with $I=1,\ldots,N_x$ components can be astronomical. For example, With $N_{xx}=22$ for *EOSxx*(22) and $N_x=9$ for *EOSx*(9), there are $N_{EOSx}=1.8\cdot10^{11}$ possible lumping schemes[3],

$$N_{EOSx} = \frac{N_{xx}!}{(N_{xx}-N_x)!} \quad (1)$$

If one only allows lumping of contiguous original components into contiguous pseudo-components, the number of possible lumped EOS models is less,

$$N_{EOSx} = \frac{(\tilde{N}_{xx}-1)!}{(\tilde{N}_{xx}-\tilde{N}_x)!(\tilde{N}_x-1)!} \quad (2)$$

where $\tilde{N}_{xx}$=number of original components in the *EOSxx* model that can be lumped, and $\tilde{N}_x$=number of pseudo-components

[2] The value of N_{xx} in Eq. 1 should only include the number of original components that are allowed to lump into pseudo-components.

[3] Eq. 1 only represents those combinations where "complete" lumping is made of original component *i* into a single pseudo-component *I* – i.e., we do not consider lumping of partial amounts of original components *i* into lumped components *I*.

that are created by lumping in the *EOSx* model. For our example with $\tilde{N}_{xx}=N_{xx}=22$ and $\tilde{N}_x=N_x=9$ a total of $N_{EOSx}=203{,}490$ lumped EOS models exist.

For another example with $N_{xx}=34$ and $N_x=15$, if the first ten light components (of 34 total) are *not* allowed to be used in lumping, only the C_{7+} fractions can be lumped, then $\tilde{N}_{xx}=(34\text{-}10)=24$. These original 24 fractions can be lumped into only $\tilde{N}_x=(15\text{-}10)=5$ pseudo-components, resulting in $N_{EOSx}=(24\text{-}1)!/[(24\text{-}5)!(5\text{-}1)!]=8{,}855$ possible lumping scenarios.

Many lumping schemes are *intuitively* illogical, e.g. lumping C_1 and C_{36+}. But many lumping schemes are difficult to rule out as bad or sub-optimal, e.g. C_2-C_3 versus C_3-C_4. What might be optimal for modeling PVT of tubing vertical flow performance might be sub-optimal for describing reservoir processes. It is unlikely that any set of empirical or heuristic guidelines can be found to identify optimal component lumping. Some guidelines are possible to eliminate "bad" lumping for any process – e.g. lumping C_1 and C_{36+}, thereby leaving only lumping combinations that might be optimal.

Proposed Lumping Strategy

Our approach to component lumping and development of a pseudoized *EOSx* has the following steps:

1. Start with an accurate, detailed EOS model (*EOSxx*) and at least one, but preferably a set of fluid compositions described with the *EOSxx* component slate.
2. Define the range of *p-T-z* relevant to the processes being modeled, including a range of samples that cover the low-to-high gas-oil ratios (GORs) of relevant fluids.
3. Calculate all relevant PVT properties (densities, viscosities, compositions, phase fractions) with the detailed *EOSxx* for the entire range of relevant *p-T-z* defined in step (2).
4. Input the *EOSxx*-calculated PVT results[4] in step (3) as "data" into the EOS-based PVT program.
5. Specify the desired number (N_x) of components in the pseudoized *EOSx*, and any constraints on the lumping strategy: define lumping component numbers $\tilde{N}_{xx}$ and $\tilde{N}_x$.
6. Define the total lumping combinations with Eq. 2.
7. Use an algorithm for generating the N_{EOSx} scenarios; we took an algorithm from an open source Ruby script by Matsumoto (1993), somewhat modified for the lumping application.
8. For each lumping scheme, use a reliable method to calculate *EOSx* average pseudo-component properties based on a single "averaging" composition $\underline{z}_i$.[5]
9. For each new lumping scheme, use all of the PVT "data" defined in step (3) and calculate a weighted measure of model accuracy – e.g. a weighted root mean square (RMS).
10. Identify the lumping scheme(s) that give the best model match (lowest RMS).
11. The process can be repeated using different averaging methods and different averaging composition $\underline{z}_i$ in step (8).
12. Evaluate, in detail, the PVT calculations of the final *EOSx* model(s) with lowest RMS, comparing with results from the original *EOSxx* model. Plot and compare tables of key data.
13. If MMP is of particular importance (or other more-complex calculations than could be included in the global search because of CPU limitations), select a subset of the scenarios from the global search (100-500) with lowest RMS values for PVT predictions. Run MMP calculations for these scenarios and compare with MMP from the *EOSxx* model, to select a best combination of PVT fit (low RMS) and prediction accuracy of the MMP (e.g. +/- 10 psi).

"Original" (Detailed) *EOSxx* Model

One starts with an original, detailed *EOSxx* that describes experimental PVT data of the fluid system over a comprehensive range of measured pressure, temperature, and composition (*p-T-z*). Typically, such a model is developed by tuning procedures to minimize the difference between measured PVT data and the *EOSxx* model for one or many samples from the reservoir fluid system. The data might include depletion, multi-stage separation, and gas injection tests. Preferably many samples are used in the *EOSxx* model tuning, with PVT data representing the changes in pressure, temperature, and composition expected during reservoir recovery processes, transportation, and surface processing.

Bottomline, the *EOSxx* model is assumed to accurately describe the PVT behavior of all fluids found in the production system

[4] The *EOSxx* versus *EOSx* RMS calculation is made excluding viscosities. Once an optimal lumped *EOSx* has been developed with acceptable PVT accuracy, viscosities of *EOSxx* and *EOSx* are compared. If *EOSx* viscosities need improvement, appropriate viscosity tuning of the final *EOSx* can be made – e.g. tuning the heavy component critical volumes with the LBC viscosity model in a separate regression.

[5] Most published methods for calculating lumped pseudo-component properties (M, p_c, T_c, ω) and pseudo-component binary interaction parameters (BIPs) follow the guidelines given by Coats in 1985. Different methods to average lumped EOS properties have been published, e.g. Leibovici (1993). Our work uses the proprietary and unpublished methods found in *PhazeComp*. Regardless of the averaging method used, a single composition ($\underline{z}_i$) must be selected to do the averaging.

from reservoir to process to transportation for a wide range of conditions of pressure and temperature through which the fluids flow.

The Averaging Composition

The composition ($\underline{z}_i$) used to average pseudo-component properties in the lumped *EOSx* model is chosen heuristically, but it is often one of the reservoir fluid compositions with measured PVT. It might be an average of several reservoir fluid compositions.

Theoretically the averaging composition could be *any* composition that gives the best overall match between *EOSx* and *EOSxx*. As such, one could optimize this composition as part of the overall lumping process. Though we do not optimize the averaging composition in this work, we may try different reservoir compositions as the averaging composition to find the one that gives the best overall *EOSx* description. Sometimes the best averaging composition is associated with the fluid(s) that exhibit the most-complex phase behavior – e.g. an oil sample that is undergoing multi-contact miscibility, or the most near-critical composition in a compositionally-grading system. Some trial-and-error is recommended to assess the impact of averaging composition on the final *EOSx*. Also, one must decide whether to conserve mass or moles when lumping compositions other than the averaging composition $\underline{z}_i$; we conserve mass in our study.

Defining Relevant *p-T-z* Range

A collection of samples is selected, covering the entire range of reservoir fluid compositions (e.g. in terms of C_{5+} molar amount). We typically choose from 3 to 6 reservoir samples. The sample compositions are given in terms of the original *EOSxx* component slate. For each sample, a wide range of PVT calculations are made using *EOSxx*: (1) depletion tests such as constant composition expansion (CCE), differential liberation, or constant volume depletion; (2) multi-stage separator tests are simulated for each reservoir sample, and possibly some of the calculated depletion equilibrium gas and oil mixtures; and (3) for relevant injection gases, we generate a comprehensive swelling test with CCE for each oil/injection-gas mixture, sometimes a vaporization test, and in some cases a minimum miscibility pressure (MMP).

The simulated PVT data represent our "data base" for comparison with any lumped *EOSx* model: i.e. PVT(*EOSxx*) vs PVT(*EOSx*). The typical depletion PVT data used in the comparison include phase volumes (below saturation pressure), phase densities, and phase viscosities. Separator test data include oil-gas ratio (OGR) and gas-oil ratio (GOR), stock-tank oil density or API, primary separator gas gravity, and oil shrinkage at each stage.

Gas Injection Tests. Gas injection PVT data include multiple CCE tests of each mixture in a comprehensive swelling test that adds incremental amounts of an injection gas to the original oil. Each mixture saturation conditions are determined, with single- and two-phase volumes, densities and viscosities calculated. We try to have at least three bubblepoint mixtures, three dewpoint mixtures, and two of these mixtures just on each side of the critical transition from bubblepoint-to-dewpoint.

The vaporization test used for gas injection projects not achieving miscibility but recovering significant extra oil by a vaporization process requires, as shown by Coats (1985), at least 3-5 C_{7+} fractions. The reason is that lighter C_{7+} fractions (e.g. C_{7-12}) vaporize more efficiently than heavier C_{7+} fractions (e.g. C_{20+}). Multiple C_{7+} fractions are needed to correctly predict the varying recovery efficiency of vaporization for the many C_{7+} fractions in an oil or retrograde condensate.

MMP Calculations. For miscible gas injection processes, MMP[6] predicted by the original *EOSxx* should be similar with the MMP predicted by the lumped *EOSx* model, for the relevant injection gases in a field development. We have not generally used an MMP calculation data as part of the lumping strategy, because of significantly-longer CPU time to compute the MMP (10-20 times longer than a large suite of standard PVT tests taking ~0.15 s CPU). Sometimes, however, we do include an MMP calculation to help refine the search for an optimal lumping strategy that emphasizes more directly the developed miscibility process; see Examples 2 and 3 below.

Compositional Data. Ideally one would like to use calculated phase equilibrium compositions from the *EOSxx* model as a contribution to the optimal lumping search. For example, incipient compositions from saturation pressures, and separator gas compositions. This was not considered in the work presented here. The basic problem is re-defining the compositional data (from *EOSxx*) differently for each lumping scenario considered. PhazeComp does not automatically lump input compositional data used in defining its RMS, so treating this problem consistently would require pre-processing calculated compositional data (from *EOSxx*), differently for each lumping scenario. We hope to implement this capability in the future.

Optimal Lumped *EOSx* Model Tuning – RMS Criterion

[6] The MMP used here is calculated by PhazeComp and represents the lowest minimum miscibility pressure that can be achieved by a multi-contact displacement – e.g. as would be determined by a 1D (slimtube-type) displacement. The displacement mechanism is usually (and for all cases in this paper) the condensing/vaporizing MMP (Zick, 1986).

A measure of "accuracy" between the original *EOSxx* model and the lumped *EOSx* model is needed to rank different lumping scenarios. Denoting d_{xx} as PVT data calculated with *EOSxx* and d_x as calculated results from a lumped *EOSx*, the total model mismatch is given by an root mean square (RMS) with residuals defined as $r_n=100(d_{x,n}-d_{xx,n})/d_{ref,n}$. The reference data value (d_{ref}) is taken as the maximum of all d_{xx} data of a given type (e.g. oil density) in a given simulated lab test (e.g. CCE):

$$RMS = \bar{r} = \left[\frac{\sum_{n=1}^{N_{data}}(w_n r_n)^2}{\sum_{n=1}^{N_{data}} w_n^2}\right]^{0.5} \quad \text{.....(3)}$$

Weighting factors w_n are, by default, 1 but can be changed to reflect the relative importance of a particular data, and the number of data of a given type.

The *EOSxx-vs-EOSx* RMS value is used to gauge the accuracy of the lumped and original EOS models. Clearly, the measure of accuracy depends on the number and type of simulated data, and their weighting factors. Defining the RMS is perhaps the most challenging step in our approach to optimal lumping, and it is certainly the most important aspect of finding a lumped *EOSx* model that honors the specifics of a particular fluid system.

Conceivably one can develop several lumped *EOSx* models, each optimal for a particular application, e.g. an *EOSx* for *reservoir*, another *EOSx* for *flow assurance*, and yet another *EOSx* for *processing facility*. The originating *EOSxx* model used to develop the different *EOSx* lumped models is likely to be the same[7], but the number of pseudo-components might vary for each application, together with the sub-space of *p-T-z* where *EOSxx* data are generated to define the RMS.

Component Lumping Strategy

The possible number of lumped *EOSx* models originating from a detailed *EOSxx* model is more than practical to consider, as given by Eq. 1. The number is even larger (infinite) if one considers partial lumping of components, where an originating component *i* can lump partially into several lumped pseudo-components *I*. To reduce the number of possible lumping schemes we introduce a few constraints on lumping.

1. Light, pure component lumping of non-hydrocarbons with hydrocarbons methane through n-pentane can be, optionally, restricted: e.g. N_2 only with C_1, CO_2 only with C_2, or H_2S only with C_3.
2. Hydrocarbons are lumped only by contiguous carbon numbers, e.g. $C_7C_{10}=C_7+C_8+C_9+C_{10}$. The following lumped pseudo-components would *not* be allowed: $C_7C_{10}=C_7+C_{10}$ and $C_8C_9=C_8+C_9$. For isomers with the same carbon number, we recommend contiguous ordering of the original components by normal boiling point (NBP), as is normally done by PVT laboratories; lumping would then be done using contiguous NBP-ranked components.
3. Unconstrained partial lumping is not allowed. Normally, *all* of an original component *i* is contained in a single lumped component *I*. One exception for partial lumping would be a user-specified and fixed amount of original component *i* is distributed to several lumped components I_1, I_2, etc – e.g. 70% of n-C_5 in lumped pseudo-component C_5C_6 and 30% of n-C_5 in lumped pseudo-component C_5C_7.

Examples

We give an example following the lumping guidelines described above. The initial detailed *EOSxx(34)* model is shown in **Table 1**, with total components N_{xx}=34. The Peng-Robinson EOS is used, with the Lorentz-Bray-Clark (1964) viscosity correlation.[8] Eleven "light" components include the two non-hydrocarbons N_2 and CO_2, with traditional two-isomer description of butanes (i-C_4, n-C_4) and pentanes (i-C_5, n-C_5). Single-carbon number (SCN) heavier fractions range from C_6 to C_{29}, with the heaviest fraction being C_{30+}.

Five reservoir fluids were generated from a reference gas condensate composition using the isothermal chemical-gravity segregation model (Whitson and Belery, 1994). Five fluids were selected to conduct PVT simulations using the detailed *EOSxx(34)* model: a *lean gas condensate* (LGC) with 50 STB/MMscf solution oil-gas ratios (OGR); a *richer gas condensate* (RGC) with 100 STB/MMscf; a *near-critical oil* (NCO) with 5000 scf/STB solution GOR (200 STB/MMscf OGR); a *more-volatile oil* (MVO) with solution GOR of 2200 scf/STB, and a *less-volatile oil* (LVO) with solution GOR of 1000 scf/STB. The molar and mass compositions of these five reservoir fluids are given in **Table 2** using the *EOSxx(34)* component slate.

[7] If different original *EOSxx* models exist for each application where a lumped *EOSx* is required, then the *EOSxx* used to create data for each application would be different, as well as the *p-T-z* sub-space particular to that application.

[8] A default PhazeComp fluid characterization was used to generate the *EOSxx* model. The input data for this and other fluid models developed in this paper are available upon request. The PhazeComp program can be downloaded from www.zicktech.com and used without license fee for up to one month, allowing anyone to evaluate the details of calculations presented in this work.

For each of the five samples, a CCE and a 3-stage separator test were simulated with the detailed *EOSxx*(34) model. The more-volatile oil sample was subjected to a comprehensive swelling test using first-stage separator gas resulting from the 3-stage separation of the same MVO sample. Three bubblepoint oil mixtures and three dewpoint gas mixtures were created by adding, respectively, the following moles of injection gas (per mole initial oil): 30, 60, 90, 100, 150, 200%. Some 1200 data form the basis for developing optimal lumped pseudoized *EOSx* models.

Weighting factors were selected manually to balance (1) the number of data for various property types (e.g. fewer saturation pressures versus oil densities), (2) the relative importance of particular data types (e.g. saturation pressures and separator test stock-tank oil volumes). A complete listing of weighting factors can be ascertained from the PhazeComp data set made publically available from this study, with key global weight factors given in **Table 3**.

Table 4 and **Figs. 7-13** present the PVT calculations using *EOSxx(34)*.

Example 1 – Lumped EOSx(15). The first lumping scheme was to N_x=15 total components, with all lighter components kept intact, and five C_{7+} fractions lumped from the 24 original *EOSxx(34)* C_{7+} fractions. Consequently, $\tilde{N}_{xx}$=24 C_{7+} fractions can be lumped into $\tilde{N}_x$=5 pseudo-components, resulting in 8,855 lumping scenarios.This particular lumping scheme would likely contain too many components for large-scale compositional reservoir simulation, but we want to illustrate what effect C_{7+}-only lumping has on PVT model quality.

Figs. **1-2** show RMS versus scenario number, where RMS defines the mismatch of *EOSx(15)* versus *EOSxx(34)*. A clear trend in "best quality" is defined by the locus of lowest RMS values shown as a gray line. The final best *EOSx*(15) model (with lowest RMS) has the set of lumped C_{7+} components shown in **Table 5**, together with the four other best lumped EOS models.

In this example the five best C_{7+} fractions are: *Fraction 1* – C_7-C_{9-10}; *Fraction 2* – C_{10-11}-C_{13-15}; *Fraction 3* – C_{14-16}-C_{19-22}; *Fraction 4* – C_{20-23}-C_{29}; *Fraction 5* – C_{30+}. All of the best lumped EOS models use C_{30+} as the heaviest fraction. Keeping the heaviest fraction without lumping it together with lighter fractions is often what we find gives the most accurate description of more-complex phase behavior such as MMP and critical transitions in swelling tests. The predicted MMPs for the five best *EOSx(15)* models are within 0.5% of the *EOSxx(34)* MMP=3660 psia.

Example 2 – Lumped EOSx(9). The second lumping scheme was to N_x=9 total components. Non-hydrocarbons N_2 and CO_2 were kept as pure compounds, as was methane. Otherwise, a global search was made for optimal lumped components starting with ethane, with the restriction that only contiguous original *EOSxx* components would be lumped in their entirety into a lumped *EOSx* component. Given that $\tilde{N}_{xx}$=34-3=31 original components can be lumped into $\tilde{N}_x$=9-3=6 pseudo-components, a total of 142,506 lumping scenarios exist.

Figs. 3-4 show RMS versus scenario number, where RMS defines the mismatch of *EOSx(9)* versus *EOSxx(34)*. A clear trend in "best quality" is defined by the locus of lowest RMS values for scenarios ~36,000. The final best *EOSx*(9) model with lowest RMS (#35,847) has the set of lumped components shown in **Table 6**, together with the four other best (lowest-RMS) lumped EOS models. Fig.4 and Table 6 also show two lumping scenarios (#53,395 and #12,074) that are at "local" minima, one on each side of the global lowest-RMS scenario.

MMP Emphasis. For the lowest-RMS scenario (#35,847), the predicted MMP is low by 2% compared with the *EOSxx(34)* MMP of 3660 psia. This is a higher deviation than desired, so we ask the question whether any of the other "very-good" lumping scenarios (i.e. with low RMS values) might have an accurately predicted MMP.

We added a single MMP calculation for the more-volatile oil sample using the same injection gas as in the swelling test. Including the single MMP data during a global lumping search with 142,506 possible scenarios would have increased the run time from about ~10 hr (0.15 s/scenario) to ~160 hr (2.5 s/scenario). This was unreasonable, so we used another approach to search for an optimal lumping scenario with good MMP prediction.

First we identified the RMS value from the global search that yields an adequate description of the key 1200 PVT data. For this example we used the scenarios that kept an RMS<2%, satisfied by about 500 lumping scenarios. We reran these scenarios again, but now including the MMP calculation. Only ten of the 500 lumping scenarios resulted in an MMP within 10 psi of the *EOSxx* MMP. Scenario (#34,458) had the best MMP match (within 0.4 psi) *and* the lowest RMS (of the ten scenarios), thereby making this particular scenario the obvious "best" lumping scheme for *EOSx(9)*.

For the overall best scenario (#34,458), the five plus fractions are: *Fraction 1* – *i*-C_4-C_6; *Fraction 2* – C_7-C_{11}; *Fraction 3* – C_{12}-C_{15}; *Fraction 4* – C_{16}-C_{23}; *Fraction 5* – C_{24+}. We note that *none* of the best lumped EOS models used C_{30+} as the heaviest fraction, a somewhat unexpected result. For *EOSx(9)* all of the best lumping scenarios had a heaviest fraction of C_{24+} to C_{26+},

not C_{30+}. Perhaps some of the loss in accuracy due to lumping of lighter components was compensated by the lumping of the heaviest fraction.

Example 3 – Lumped EOSx(6). The third lumping scheme was to N_x=6 total pseudo-components. A global search was made for optimal lumped components starting with non-hydrocarbons which were ordered contiguously as N_2, C_1, CO_2, C_2, C_3,i-C_4,n-C_4, i-C_5, n-C_5, C_6, …, again with the restriction that only contiguous original *EOSxx(34)* components would be lumped in their entirety into single lumped *EOSx(6)* components. Given that $\widetilde{N}_{xx}=N_{xx}$=34 original components can be lumped into $\widetilde{N}_x=N_x$=6 pseudo-components, a total of 237,336 lumping scenarios exist.

Figs. 5-6 show RMS versus scenario number, where RMS defines the mismatch of *EOSx(6)* versus *EOSxx(34)*. A clear trend in "best quality" is defined by several loci of low RMS values for scenarios ~40,000-75,000. The final best *EOSx*(6) model with lowest RMS (#45,284) has the set of lumped components shown in **Table 7**. Fig. 6 and Table 7 also show two lumping scenarios (#47,959 and #75,380) that have low RMS (within the 500 lowest) but considerably better MMP predictions. Both lumped *EOSx(6)* models with good MMP prediction have a heaviest lumped pseudo-component C_{21+}, considerably lighter than the C_{30+} of *EOSxx(34)* and somewhat lighter than C_{24+} of the lumped scenario with overall minimum RMS (#45,284).

Discussion

The key PVT property calculations using the optimal lumped *EOSx* models discussed in the three examples above are shown in Figs. 7-14. These can be compared with the original, detailed *EOSxx* model calculations. Overall, and almost without exception, the optimal lumped *EOSx* models provide very accurate PVT predictions. For the *EOSx(9)* and *EOSx(6)* optimal lumped models with accurate MMP predictions (but somewhat-higher RMS values), the PVT predictions are very good. Figs. 9-10 and Figs. 13-14 compare *EOSx* models that are optimal purely based on the RMS calculation without consideration of the MMP accuracy, versus the final optimal *EOSx* models that sacrificed somewhat on RMS of PVT but maintained an accurate MMP prediction.

Conclusions

Our proposed methodology for lumping components has the following advantages over empirical, heuristic methods typically used:

1. The method is designed to describe the physical processes (reservoir, flow assurance, process facilities, etc.) for which a lumped *EOSx* is applied.
2. The method uses a well-defined quantitative measure (weighted RMS) of the lumped *EOSx* model accuracy in terms of how well the phase and volumetric behavior compare with the original detailed *EOSxx* model.
3. The method uses a detailed *EOSxx* model that has been properly tuned to relevant laboratory PVT data to develop the pseudoized *EOSx* model. This has a major advantage in gauging the accuracy (RMS) of a particular lumped *EOSx* model because it is compared directly with the original *EOSxx* model and (not measured data). In theory, the minimum (optimal) RMS will monotonically increase in magnitude as the number of lumped components (N_x) decreases; this behavior may not exist if the lumped EOS model is fit to measured data directly.
4. Our method constrains the search for an optimal lumped EOS by allowing only contiguous components in the original *EOSxx* model to be lumped into contiguous pseudo-components in the resulting *EOSx* model.
5. The method allows user control of original components that (a) *should not be lumped*, or (b) *must be lumped* in a specific manner (e.g. *i*-C_4+*n*-C_4) – i.e. overriding the automated lumping algorithm.
6. The method makes a comprehensive search of all possible lumping scenarios, without pre-disposed (subjective) assumptions about which lumping scheme may be better.
7. Perhaps the greatest challenge in applying the proposed lumping method is (a) defining an appropriate set of data and (b) defining weighting factors for each data to reflect their importance to the processes being modeled.

Nomenclature

d_x	=	Data calculated by original *EOSxx* model.
d_{xx}	=	Data calculated by lumped *EOSx* model.
EOSx	=	A lumped (or pseudoized) EOS model developed from an original, detailed *EOSxx*.
EOSxx	=	An original, detailed EOS model properly tuned to laboratory PVT data.
i	=	Component index for original *EOSxx* model, $i=1,\ldots,N_{xx}$.
I	=	Component index for lumped *EOSx* model, $I=1,\ldots,N_x$.
MMP	=	Minimum miscibility pressure, psia.
n	=	Index of data, $n=1,\ldots,N_{data}$
N_{data}	=	Number of data used in developing lumped EOS model.
N_x	=	Total number of components in lumped *EOSx* model.
$\widetilde{N}_x$	=	Number of lumped components in lumped *EOSx* model which are created by lumping.
N_{xx}	=	Total number of components in original detailed *EOSxx* model.

$\widetilde{N}_{xx}$ = Number of components in original detailed *EOSxx* model that can be lumped.
p = Pressure.
p-T-z = Pressure-temperature-composition space.
r_n = Residual measure of deviation for data n used in RMS.
$\bar{r}$ = Root mean square, Eq. 3.
T = Temperature.
w_n = Weighting factor for data n used in RMS.
z = Molar composition.
$\underline{z}$ = Molar composition used to create lumped-component model average properties.

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TABLE 1 – EOS MODELS.

	Molecular Weight M	Critical Temperature Tc (R)	Critical Pressure Pc (psia)	Acentric Factor ω	Volume Shift s	Boiling Point Tb (R)	Specific Gravity Y	Critical Z-factor Zc(LBC)	Binary Interaction Parameters N2	C1	CO2
EOSxx(34)											
N2	28.01	227.16	492.84	0.0370	-0.1676	139.0	0.2834	0.2918			
C1	16.04	343.01	667.03	0.0110	-0.1500	200.8	0.1461	0.2862	0.025		
CO2	44.01	547.42	1069.51	0.2250	0.0019	332.8	0.7619	0.2743	0.000	0.105	
C2	30.07	549.58	706.62	0.0990	-0.0628	332.0	0.3298	0.2792	0.010	0.000	0.130
C3	44.10	665.69	616.12	0.1520	-0.0638	415.7	0.5098	0.2763	0.090	0.000	0.125
I-C4	58.12	734.13	527.94	0.1860	-0.0620	470.7	0.5704	0.2820	0.095	0.000	0.120
N-C4	58.12	765.22	550.56	0.2000	-0.0539	490.7	0.5906	0.2739	0.095	0.000	0.115
I-C5	72.15	828.70	490.37	0.2290	-0.0565	542.1	0.6295	0.2723	0.100	0.000	0.115
N-C5	72.15	845.46	488.78	0.2520	-0.0293	556.8	0.6359	0.2684	0.110	0.000	0.115
C6	82.42	924.03	489.98	0.2399	-0.0026	606.4	0.7028	0.2702	0.110	0.000	0.115
C7	96.10	990.77	454.06	0.2753	0.0137	661.2	0.7370	0.2655	0.110	0.0259	0.115
C8	108.94	1043.64	421.23	0.3113	0.0279	707.7	0.7583	0.2613	0.110	0.0298	0.115
C9	122.09	1093.72	388.43	0.3517	0.0506	754.3	0.7750	0.2570	0.110	0.0339	0.115
C10	135.01	1138.11	360.17	0.3917	0.0716	797.1	0.7884	0.2532	0.110	0.0378	0.115
C11	147.85	1178.35	335.50	0.4314	0.0912	837.1	0.7997	0.2497	0.110	0.0415	0.115
C12	160.59	1215.08	313.89	0.4709	0.1093	874.5	0.8094	0.2465	0.110	0.0449	0.115
C13	173.24	1248.80	294.88	0.5058	0.1261	909.7	0.8180	0.2434	0.110	0.0480	0.115
C14	185.78	1279.91	278.07	0.5424	0.1417	942.8	0.8257	0.2404	0.110	0.0510	0.115
C15	198.22	1308.75	263.14	0.5783	0.1560	974.1	0.8327	0.2375	0.110	0.0537	0.115
C16	210.55	1335.60	249.83	0.6135	0.1692	1003.6	0.8391	0.2347	0.110	0.0563	0.115
C17	222.77	1360.66	237.91	0.6479	0.1813	1031.6	0.8450	0.2320	0.110	0.0587	0.115
C18	234.88	1384.16	227.20	0.6816	0.1924	1058.1	0.8504	0.2294	0.110	0.0609	0.115
C19	246.87	1406.24	217.53	0.7145	0.2025	1083.2	0.8555	0.2268	0.110	0.0629	0.115
C20	258.75	1427.05	208.78	0.7467	0.2118	1107.2	0.8602	0.2243	0.110	0.0648	0.115
C21	270.52	1446.72	200.83	0.7782	0.2203	1130.0	0.8647	0.2218	0.110	0.0666	0.115
C22	282.18	1465.35	193.58	0.8090	0.2281	1151.7	0.8688	0.2195	0.110	0.0683	0.115
C23	293.73	1483.03	186.96	0.8391	0.2352	1172.5	0.8728	0.2171	0.110	0.0698	0.115
C24	305.17	1499.86	180.89	0.8684	0.2417	1192.3	0.8766	0.2149	0.110	0.0713	0.115
C25	316.50	1515.89	175.31	0.8971	0.2476	1211.3	0.8801	0.2127	0.110	0.0726	0.115
C26	327.73	1531.20	170.17	0.9252	0.2529	1229.5	0.8835	0.2105	0.110	0.0739	0.115
C27	338.86	1545.84	165.41	0.9526	0.2578	1247.0	0.8868	0.2084	0.110	0.0751	0.115
C28	349.89	1559.87	161.01	0.9793	0.2623	1263.7	0.8899	0.2064	0.110	0.0762	0.115
C29	360.82	1573.32	156.92	1.0055	0.2663	1279.9	0.8929	0.2044	0.110	0.0772	0.115
C30+	496.34	1711.84	121.96	1.2977	0.2940	1446.5	0.9235	0.1831	0.110	0.0867	0.115
EOSx(15) C7+ Fractions – Scenario 4,587 (best RMS)											
C7_C10	114.12	1063.29	405.39	0.3293	0.0418	726.7	0.7647	0.2591	0.11	0.03195	0.115
C11_C15	170.29	1240.47	298.46	0.4981	0.1240	901.5	0.8161	0.2437	0.11	0.04756	0.115
C16_C21	236.73	1387.28	225.46	0.6873	0.1946	1061.9	0.8513	0.2286	0.11	0.06131	0.115
C22_C29	315.53	1514.31	175.79	0.8948	0.2470	1209.5	0.8800	0.2125	0.11	0.07255	0.115
C30+	496.34	1711.84	121.96	1.2977	0.2940	1446.5	0.9235	0.1831	0.11	0.08672	0.115
	Molecular Weight M	Critical Temperature Tc (R)	Critical Pressure Pc (psia)	Acentric Factor ω	Volume Shift s	Boiling Point Tb (R)	Specific Gravity Y	Critical Z-factor Zc(LBC)	Binary Interaction Parameters N2	C1	CO2
EOSx(9) – Scenario 34,458 (best MMP in 500 lowest-RMS scenarios)											
N2	28.01	227.16	492.84	0.0370	-0.1676	139.0	0.2834	0.2918	0.0000		
C1	16.04	343.01	667.03	0.0110	-0.1500	200.8	0.1461	0.2862	0.0250		
CO2	44.01	547.42	1069.51	0.2250	0.0019	332.8	0.7619	0.2743	0.0000	0.1050	
C2_C3	35.89	599.88	664.14	0.1217	-0.0633	367.8	0.4287	0.2778	0.0494	0.0000	0.1275
I-C4_C6	68.59	827.97	512.77	0.2221	-0.0339	538.2	0.6364	0.2721	0.1032	0.0000	0.1154
C7_C11	119.55	1083.18	391.57	0.3465	0.0519	745.6	0.7713	0.2572	0.1100	0.0338	0.1150
C12_C15	177.67	1259.66	288.37	0.5194	0.1327	921.5	0.8209	0.2421	0.1100	0.0492	0.1150
C16_C23	245.49	1403.18	218.35	0.7116	0.2023	1080.2	0.8551	0.2265	0.1100	0.0629	0.1150
C24_C30+	444.01	1662.89	133.32	1.1885	0.2848	1387.2	0.9139	0.1892	0.1100	0.0838	0.1150
	Molecular Weight M	Critical Temperature Tc (R)	Critical Pressure Pc (psia)	Acentric Factor ω	Volume Shift s	Boiling Point Tb (R)	Specific Gravity Y	Critical Z-factor Zc(LBC)	Binary Interaction Parameters N2_C1	CO2_I-C4	
EOSx(6) – Scenario 47,959 (best MMP in 500 lowest-RMS scenarios)											
N2_C1	16.07	342.75	666.66	0.0110	-0.1500	200.7	0.1463	0.2862			
CO2_I-C4	36.99	605.65	656.08	0.1250	-0.0629	372.3	0.4400	0.2781	-0.00008		
N-C4_C6	69.61	836.64	511.23	0.2254	-0.0316	544.5	0.6417	0.2713	0.00010	-0.00006	
C7_C12	124.72	1101.27	379.04	0.3631	0.0615	763.1	0.7772	0.2554	0.03567	-0.00006	
C13_C20	209.08	1331.53	250.68	0.6108	0.1697	999.9	0.8386	0.2342	0.05637	-0.00006	
C21_C30+	411.07	1628.74	141.94	1.1168	0.2772	1346.0	0.9072	0.1933	0.08162	-0.00006	

TABLE 2 – COMPOSITIONS OF FIVE RESERVOIR FLUIDS IN EOSxx(34) FORMAT.

	LGC		RGC		NCO		MVO		LVO	
	mol-%	mass-%	mol-%	mass-%	mol-%	mass-%	mol-%	mass-%	mol-%	mass-%
N2	0.1569	0.1612	0.1384	0.1241	0.1163	0.0853	0.0905	0.0473	0.0715	0.0242
CO2	0.1824	0.2944	0.1818	0.2561	0.1759	0.2028	0.1655	0.1360	0.1604	0.0852
C1	68.8393	40.5104	64.1678	32.9539	58.0097	24.3812	48.7345	14.5941	38.2486	7.4086
C2	13.5962	14.9967	13.9881	13.4647	14.1546	11.1506	13.7704	7.7293	12.4610	4.5240
C3	7.3612	11.9070	8.0842	11.4117	8.7381	10.0947	9.1346	7.5189	8.7294	4.6476
I-C4	0.7452	1.5888	0.8568	1.5941	0.9655	1.4701	1.0513	1.1406	1.0357	0.7268
N-C4	2.7474	5.8576	3.2186	5.9885	3.7119	5.6522	4.1628	4.5164	4.1983	2.9462
I-C5	0.6341	1.6782	0.7790	1.7991	0.9387	1.7743	1.1003	1.4819	1.1482	1.0002
N-C5	1.0967	2.9025	1.3647	3.1520	1.6692	3.1552	1.9903	2.6804	2.1016	1.8307
C6	1.2279	3.7124	1.6143	4.2594	2.0917	4.5165	2.6725	4.1116	3.0233	3.0086
C7	0.8967	3.1610	1.2554	3.8617	1.7381	4.3757	2.4032	4.3108	2.9204	3.3883
C8	0.7034	2.8109	1.0383	3.6207	1.5143	4.3217	2.2157	4.5056	2.8258	3.7168
C9	0.4942	2.2131	0.7710	3.0133	1.1870	3.7966	1.8400	4.1931	2.4620	3.6291
C10	0.3573	1.7695	0.5883	2.5427	0.9543	3.3753	1.5630	3.9389	2.1892	3.5685
C11	0.2588	1.4035	0.4494	2.1267	0.7671	2.9713	1.3255	3.6581	1.9407	3.4642
C12	0.1878	1.1065	0.3437	1.7669	0.6170	2.5957	1.1232	3.3669	1.7170	3.3291
C13	0.1367	0.8685	0.2633	1.4604	0.4966	2.2540	0.9514	3.0765	1.5169	3.1728
C14	0.0997	0.6793	0.2021	1.2022	0.4002	1.9478	0.8058	2.7945	1.3389	3.0033
C15	0.0729	0.5300	0.1555	0.9866	0.3229	1.6767	0.6827	2.5260	1.1812	2.8269
C16	0.0534	0.4128	0.1198	0.8076	0.2609	1.4389	0.5787	2.2743	1.0418	2.6483
C17	0.0393	0.3211	0.0925	0.6600	0.2111	1.2318	0.4908	2.0409	0.9188	2.4713
C18	0.0290	0.2496	0.0716	0.5386	0.1710	1.0525	0.4166	1.8267	0.8106	2.2988
C19	0.0214	0.1939	0.0556	0.4392	0.1388	0.8979	0.3540	1.6315	0.7155	2.1327
C20	0.0159	0.1507	0.0432	0.3579	0.1129	0.7653	0.3012	1.4546	0.6320	1.9744
C21	0.0118	0.1171	0.0337	0.2916	0.0920	0.6518	0.2565	1.2953	0.5587	1.8247
C22	0.0088	0.0911	0.0263	0.2376	0.0750	0.5548	0.2188	1.1523	0.4943	1.6842
C23	0.0066	0.0709	0.0206	0.1936	0.0614	0.4721	0.1868	1.0243	0.4379	1.5528
C24	0.0049	0.0552	0.0162	0.1579	0.0503	0.4018	0.1598	0.9101	0.3883	1.4306
C25	0.0037	0.0430	0.0127	0.1288	0.0412	0.3419	0.1368	0.8083	0.3447	1.3173
C26	0.0028	0.0336	0.0100	0.1051	0.0339	0.2910	0.1173	0.7178	0.3064	1.2124
C27	0.0021	0.0262	0.0079	0.0859	0.0279	0.2478	0.1008	0.6374	0.2727	1.1157
C28	0.0016	0.0205	0.0063	0.0702	0.0230	0.2111	0.0867	0.5661	0.2430	1.0265
C29	0.0012	0.0161	0.0050	0.0574	0.0190	0.1799	0.0746	0.5028	0.2168	0.9444
C30+	0.0026	0.0468	0.0179	0.2838	0.1126	1.4639	0.7373	6.8307	3.3483	20.0650

TABLE 4 – SEPARATOR TEST CALCULATIONS.

Sample	LGC	RGC	NCO	MVO	LVO
Oil Properties					
R_s EOSxx(34), scf/STB			**5175**	**2283**	**986**
R_s EOSx(15)			-0.8%	-0.4%	-0.2%
R_s EOSx(9)			-3.1%	-2.4%	-1.4%
R_s EOSx(6)			0.0%	0.7%	1.2%
B_o EOSxx(34), RB/STB			**4.267**	**2.358**	**1.583**
B_o EOSx(15)			-0.6%	-0.2%	-0.1%
B_o EOSx(9)			-2.4%	-1.4%	-0.5%
B_o EOSx(6)			-4.9%	0.5%	0.6%
API EOSxx(34)	**56.1**	**55.1**	**52.7**	**48.0**	**41.7**
API EOSx(15)	-0.6%	-0.6%	-0.4%	-0.2%	0.0%
API EOSx(9)	2.0%	2.2%	2.0%	1.4%	0.9%
API EOSx(6)	-2.0%	-1.9%	-1.7%	-1.5%	-0.8%
Gas Properties					
r_s EOSxx(34), STB/MMscf	**50.6**	**98.4**			
r_s EOSx(15)	3.5%	1.7%			
r_s EOSx(9)	1.7%	2.8%			
r_s EOSx(6)	8.5%	1.3%			
b_{gd} EOSxx(34), scf/ft^3	**215.6**	**225.9**			
b_{gd} EOSx(15)	-0.2%	-0.2%			
b_{gd} EOSx(9)	0.0%	-0.3%			
b_{gd} EOSx(6)	-0.9%	-1.8%			

TABLE 3 – GLOBAL WEIGHTING FACTORS IN RMS.

Experimental Property	Weighting Factor
Depletion and Multi-stage Separator Tests	
Saturation Pressure	10
Liquid Volumes/Bo	3
Liquid Saturation	3
Liquid Density	2
Gas-Oil Ratio	2
Condensate-Gas Ratio	2
Relative Volume	1
Gas Specific Gravity	1
Gas Density	1
Gas Z-factor	1
Liquid API	1
Liquid Viscosity	0
Gas Viscosity	0
Swelling Experiment & CCE of Swollen Mixtures	
Saturation Pressure	3
Liquid Saturation	3
Relative Volume	1
Liquid Density	1
Gas Density	0.5
Gas Z-factor	0.5
Liquid Viscosity	0
Gas Viscosity	0
Some individual data may be weighted slightly different than the global default weighting factors given in this table. See the PhazeComp output file for exact weighting factors of data.	

TABLE 5 – EXAMPLE *EOSx*(15) SHOWING FIVE BEST SCENARIOS BASED ON LOWEST RMS VALUE, SEE FIG. 2.

Case no.	4587	3519	3405	4594	3510
RMS (%)	1.245	1.255	1.263	1.274	1.275
MMP (psia)	3670	3664	3668	3671	3665
3660	0.3%	0.1%	0.2%	0.3%	0.1%
	Components				
	N2	N2	N2	N2	N2
	CO2	CO2	CO2	CO2	CO2
	C1	C1	C1	C1	C1
	C2	C2	C2	C2	C2
	C3	C3	C3	C3	C3
	I-C4	I-C4	I-C4	I-C4	I-C4
	N-C4	N-C4	N-C4	N-C4	N-C4
	I-C5	I-C5	I-C5	I-C5	I-C5
	N-C5	N-C5	N-C5	N-C5	N-C5
	C6	C6	C6	C6	C6
	C7_C10	C7_C9	C7_C9	C7_C10	C7_C9
	C11_C15	C10_C14	C10_C13	C11_C15	C10_C14
	C16_C21	C15_C20	C14_C19	C16_C22	C15_C19
	C22_C29	C21_C29	C20_C29	C23_C29	C20_C29
	C30+	C30+	C30+	C30+	C30+

TABLE 6 – EXAMPLE *EOSx*(9) SHOWING FIVE BEST SCENARIOS BASED ON LOWEST RMS VALUE; ALSO TWO SCENARIOS AT LOCAL MINIMA OF RMS; ALSO, WITH BEST MMP MATCH AMONGST 500 LOWEST-RMS SCENARIOS, SEE FIG. 4.

	Best Five with Lowest RMS					Local Minima RMS		Best MMP
Case no.	35847	35846	35833	35832	35860	53395	12074	34458
RMS (%)	1.265	1.270	1.294	1.300	1.313	1.387	1.793	**1.683**
MMP (psia)	3583	3585	3587	3589	3582	3544	3552	**3661**
3660	-2.1%	-2.0%	-2.0%	-1.9%	-2.1%	-3.2%	-2.9%	**0.0%**
	N2	N2	N2	N2	N2	N2	N2	**N2**
	CO2	CO2	CO2	CO2	CO2	CO2	CO2	**CO2**
	C1	C1	C1	C1	C1	C1	C1	**C1**
	C2_C3	C2_C3	C2_C3	C2_C3	C2_C3	C2_I-C4	C2	**C2_C3**
	I-C4_C7	I-C4_C7	I-C4_C7	I-C4_C7	I-C4_C7	N-C4_C7	C3_N-C5	**I-C4_C6**
	C8_C10	C8_C10	C8_C10	C8_C10	C8_C10	C8_C10	C6_C10	**C7_C11**
	C11_C15	C11_C15	C11_C14	C11_C14	C11_C16	C11_C15	C11_C16	**C12_C15**
	C16_C25	C16_C24	C15_C25	C15_C24	C17_C25	C16_C23	C17_C25	**C16_C23**
	C26_C30+	C25_C30+	C26_C30+	C25_C30+	C26_C30+	C24_C30+	C26_C30+	**C24_C30+**

TABLE 7 – EXAMPLE *EOSx*(6) SHOWING BEST LUMPING SCENARIO BASED ON LOWEST RMS VALUE; ALSO SCENARIO WITH BEST MMP AND GOOD MMP MATCH AMONGST 500 LOWEST-RMS SCENARIOS, SEE FIG. 6.

	Best RMS	Best MMP	Good MMP
Case no.	45284	47959	75380
RMS (%)	2.016	**3.754**	3.761
MMP (psia)	3573	**3660**	3663
3660	-2.4%	**0.0%**	0.1%
	N2_C1	**N2_C1**	N2_CO2
	CO2_C3	**CO2_I-C4**	C2_I-C4
	I-C4_C7	**N-C4_C6**	N-C4_C6
	C8_C13	**C7_C12**	C7_C13
	C14_C23	**C13_C20**	C14_C20
	C24_C30+	**C21_C30+**	C21_C30+

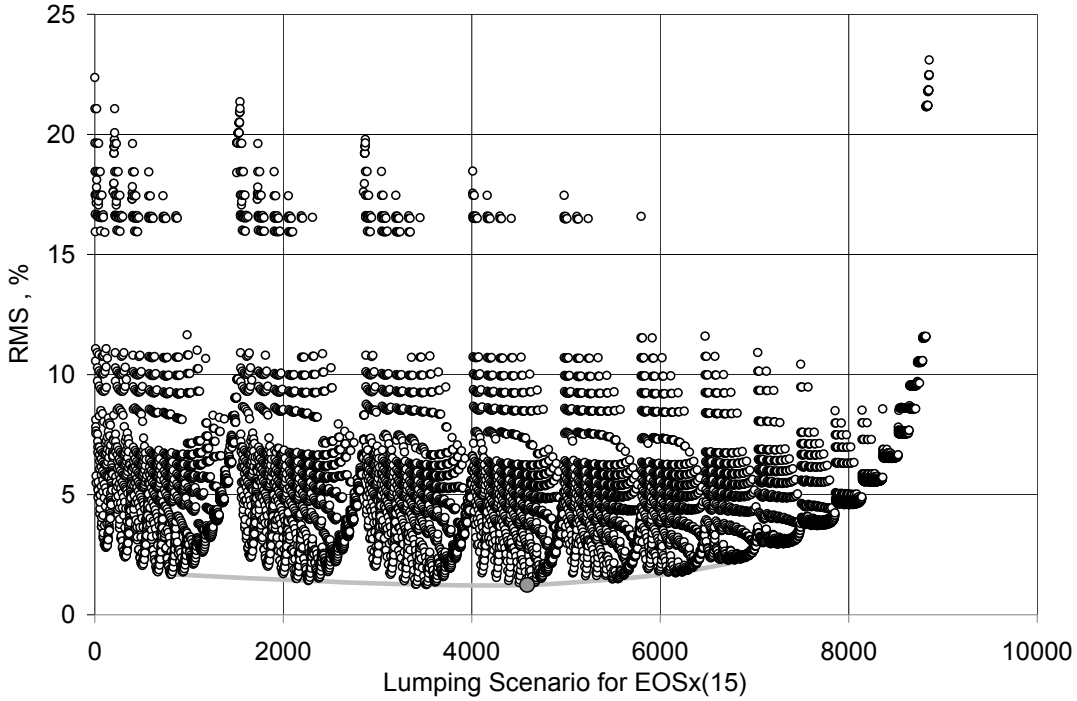

Fig. 1 – Quality of lumped *EOSx(15)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 8,855 possible lumping scenarios. Lowest RMS=Best Quality.

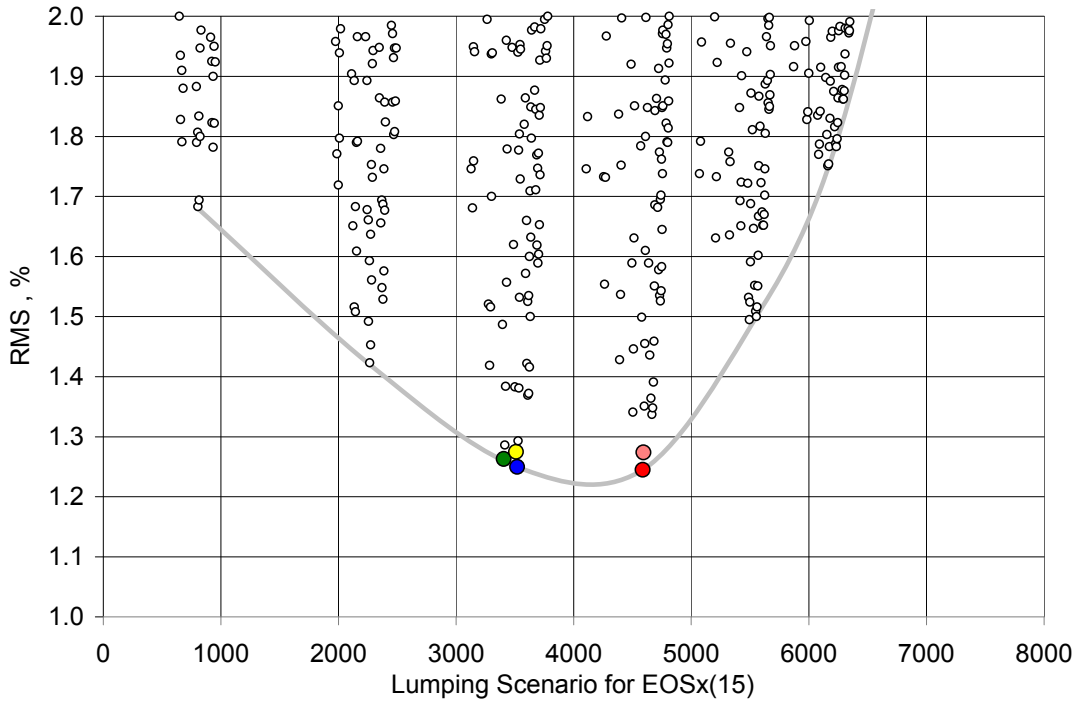

Fig. 2 – Quality of lumped *EOSx(15)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 8,855 possible lumping scenarios. Lowest RMS=Best Quality; red symbol is the global best.

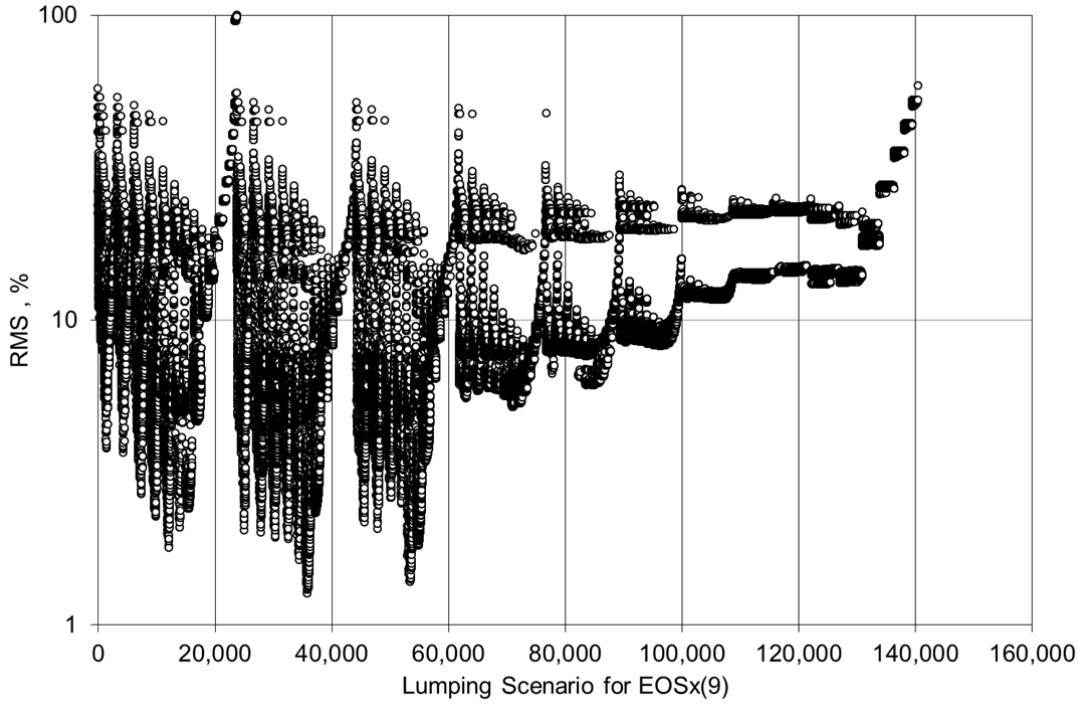

Fig. 3 – Quality of lumped *EOSx(9)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 142,506 possible lumping scenarios. Lowest RMS=Best Quality.

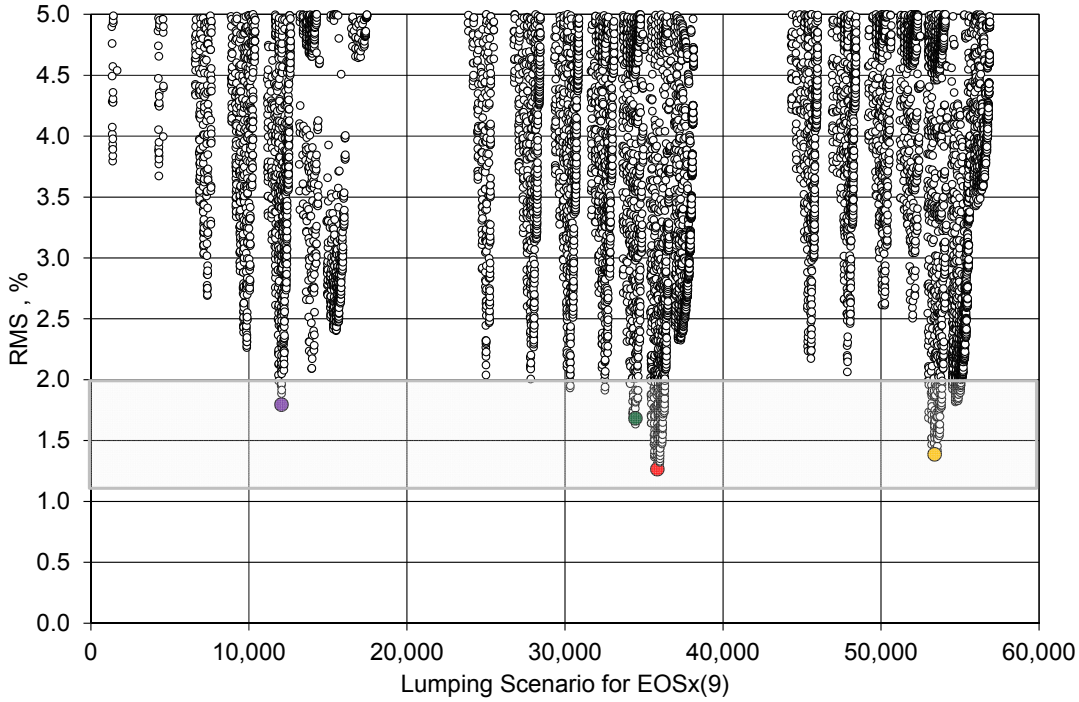

Fig. 4 – Quality of lumped *EOSx(9)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 142,506 possible lumping scenarios. Lowest RMS=best quality; red symbol is the global best based only on PVT match; purple symbol is overall best *EOSx(9)* model including close match of MMP.

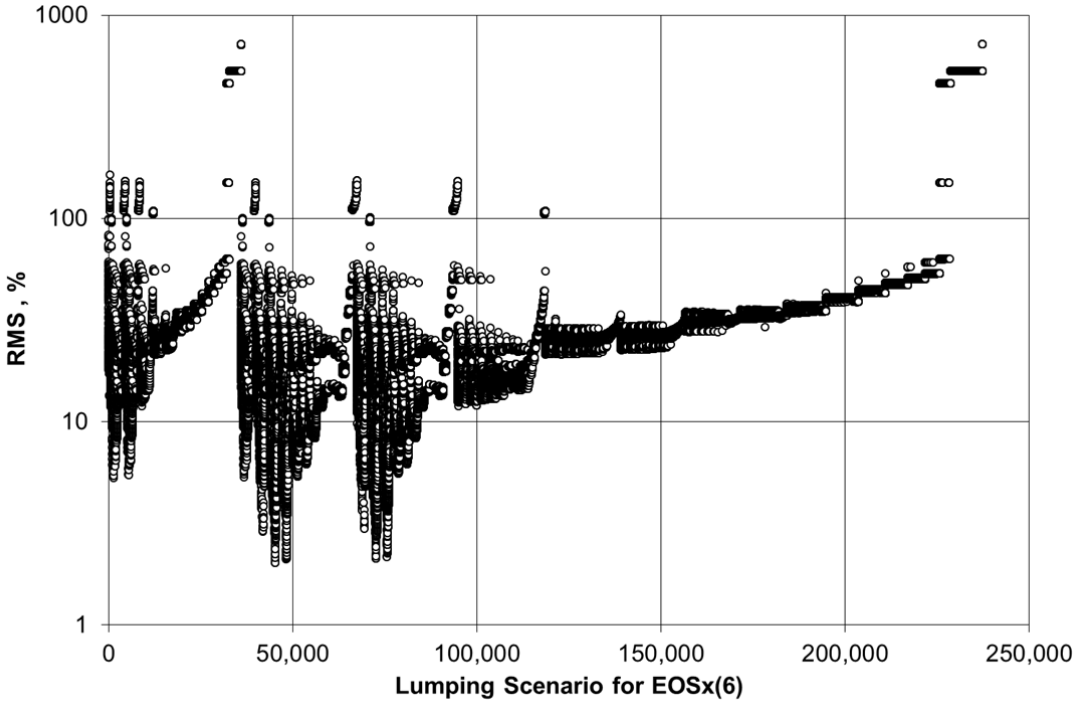

Fig. 5 – Quality of lumped *EOSx(6)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 237,336 possible lumping scenarios. Lowest RMS=Best Quality..

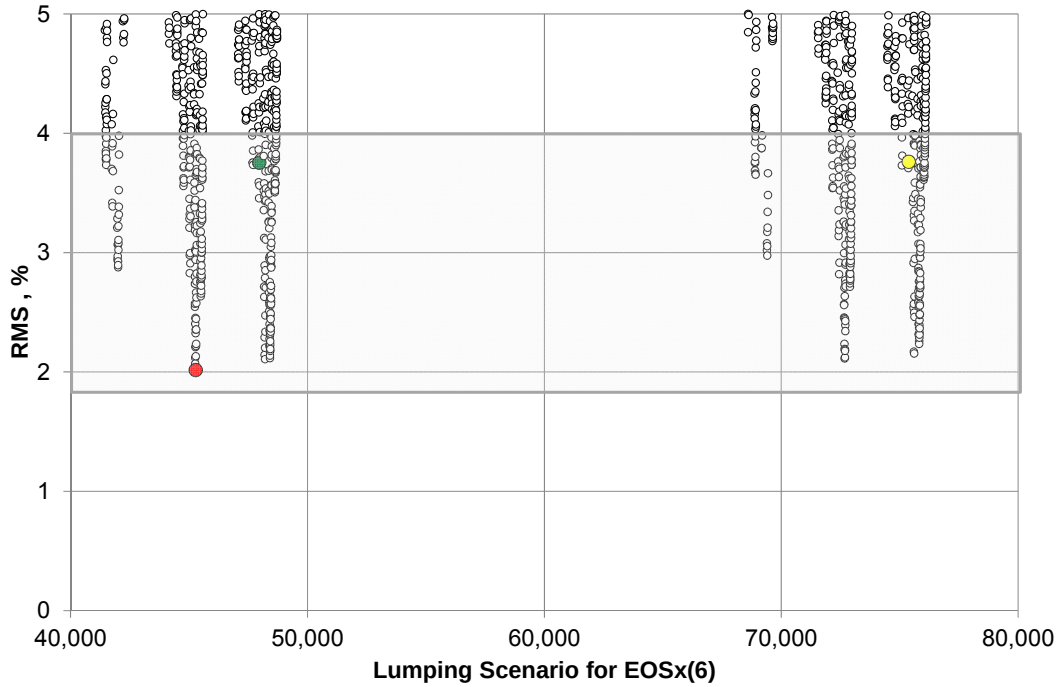

Fig. 6 – Quality of lumped *EOSx(6)* versus original *EOSxx(34)* based on 1200 PVT data during global search of 237,366 possible lumping scenarios. Lowest RMS=best quality; red symbol is the global best based only on PVT match; green symbol is overall best *EOSx(6)* model including close match of MMP; yellow symbol has a good MMP prediction (3 psi off).

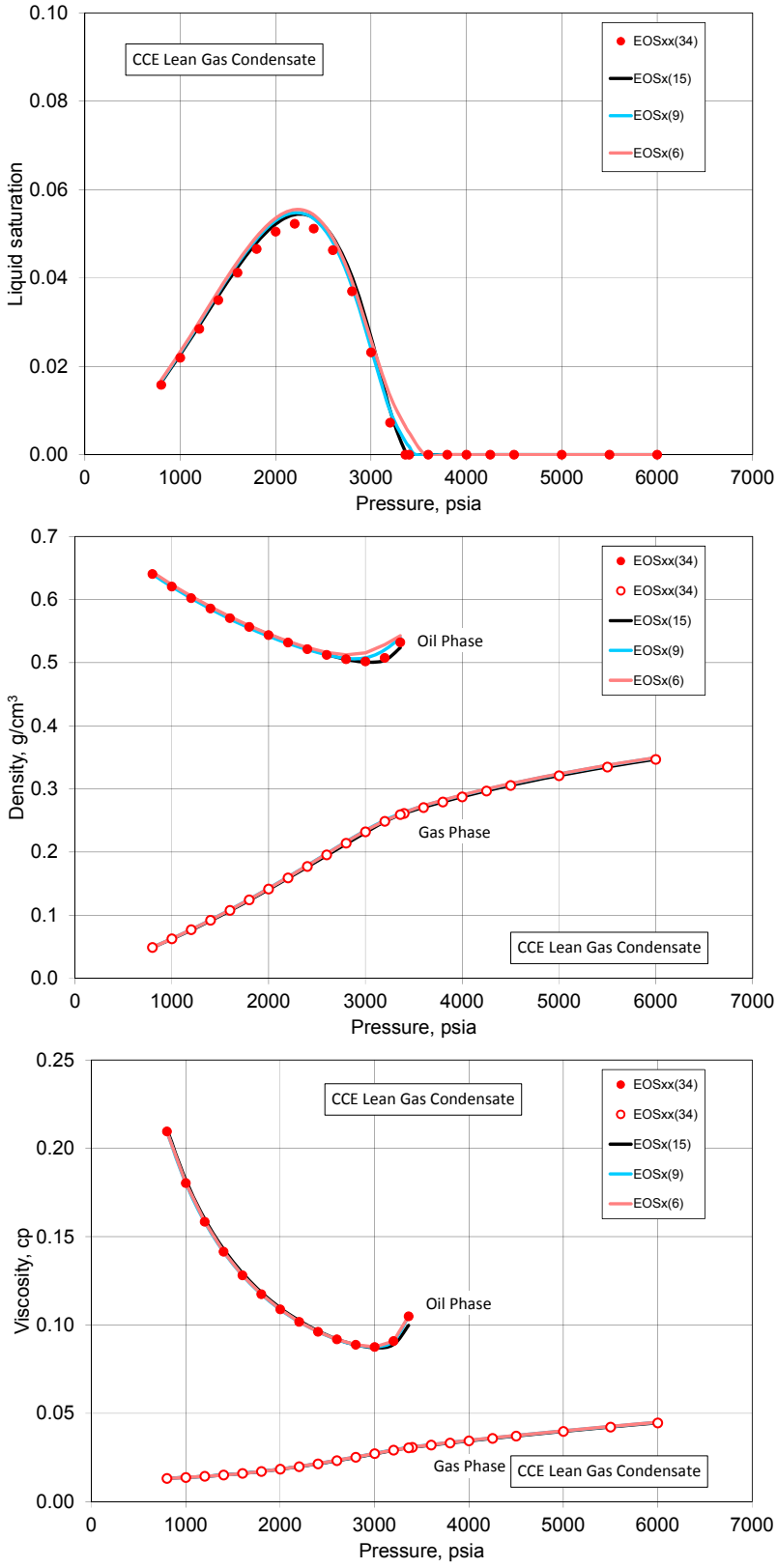

Fig. 7 – Lean Gas Condensate EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

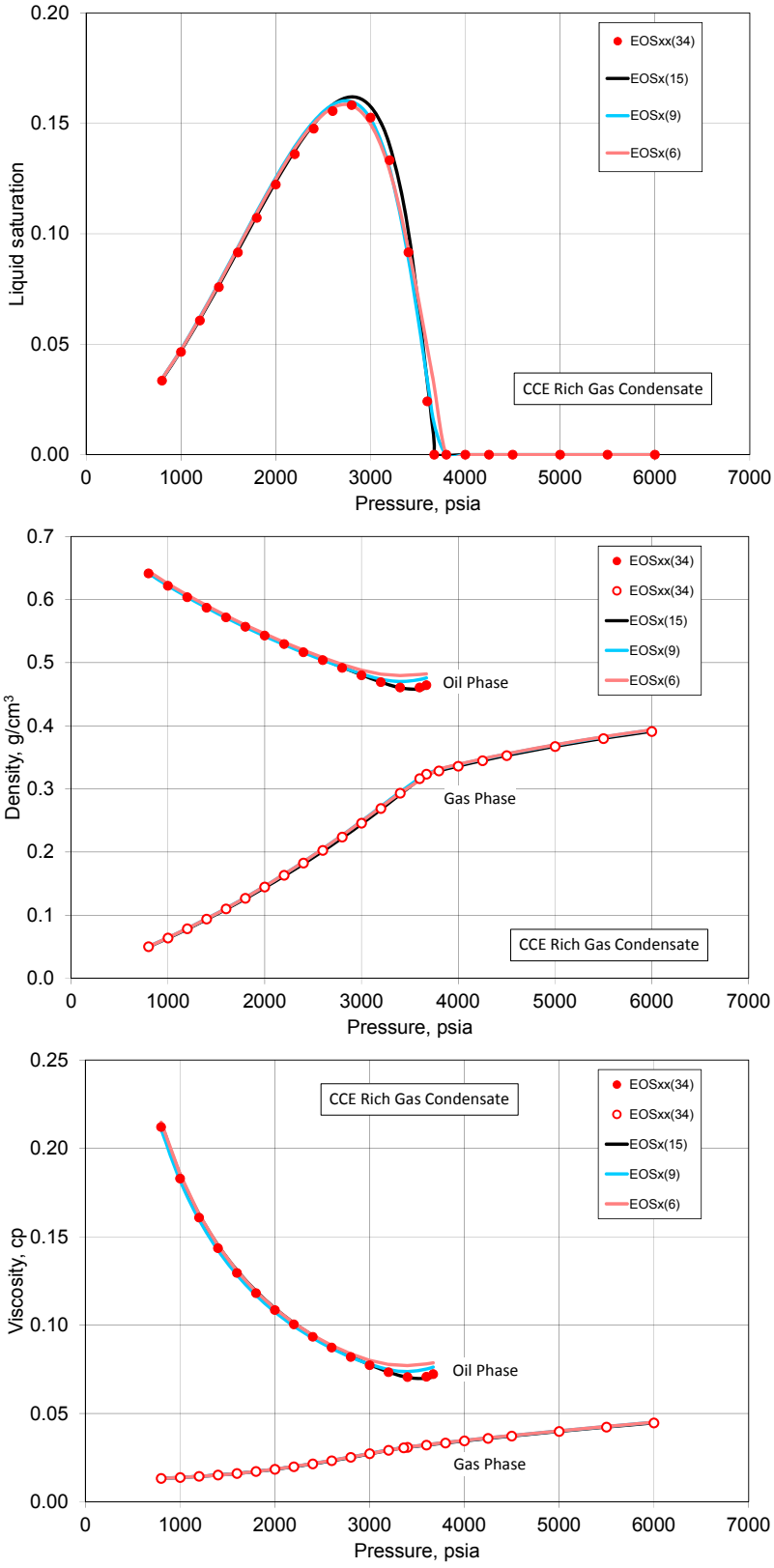

Fig. 8 – Richer Gas Condensate EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

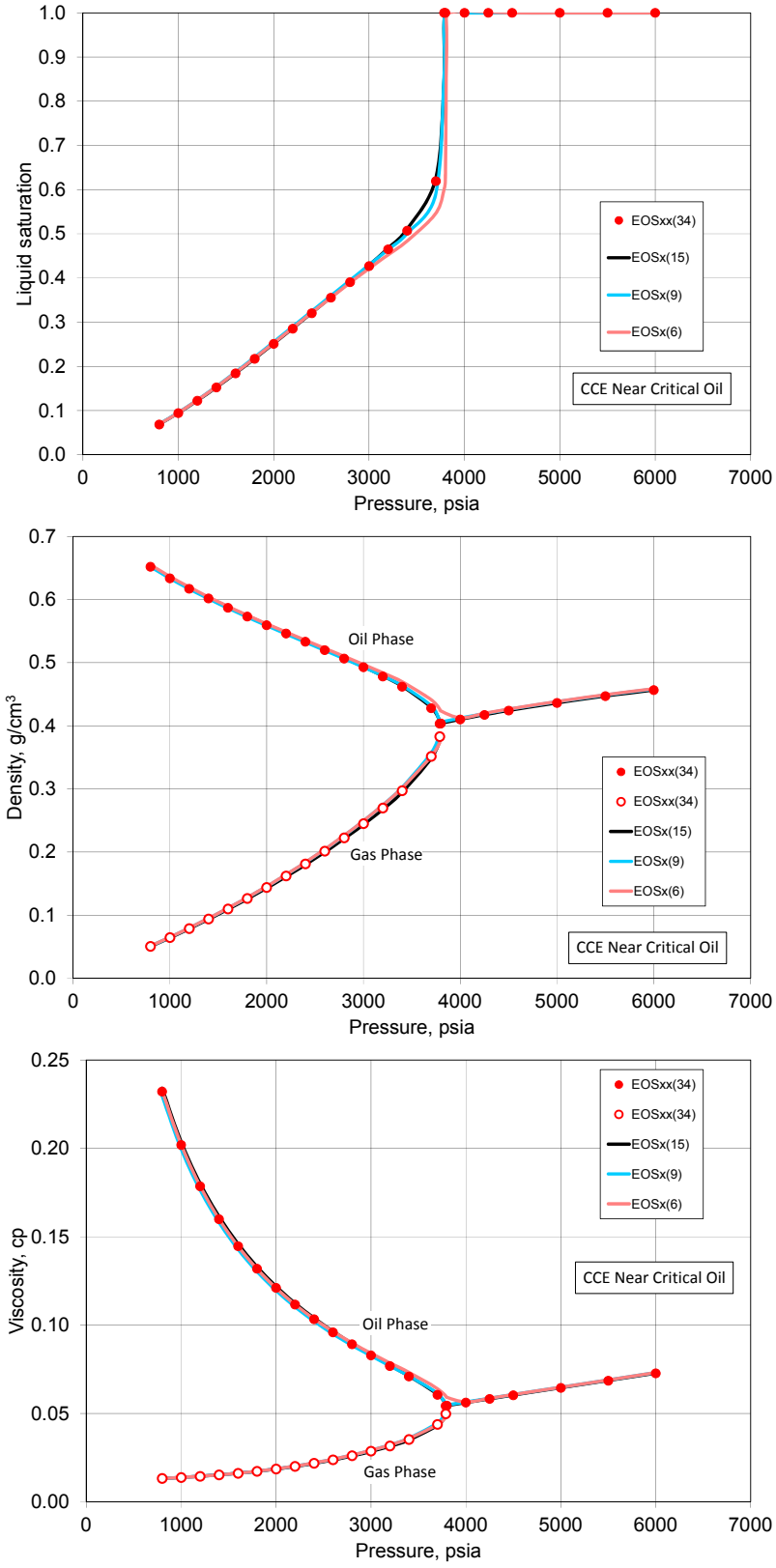

Fig. 9 – Near-Critical Oil – EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

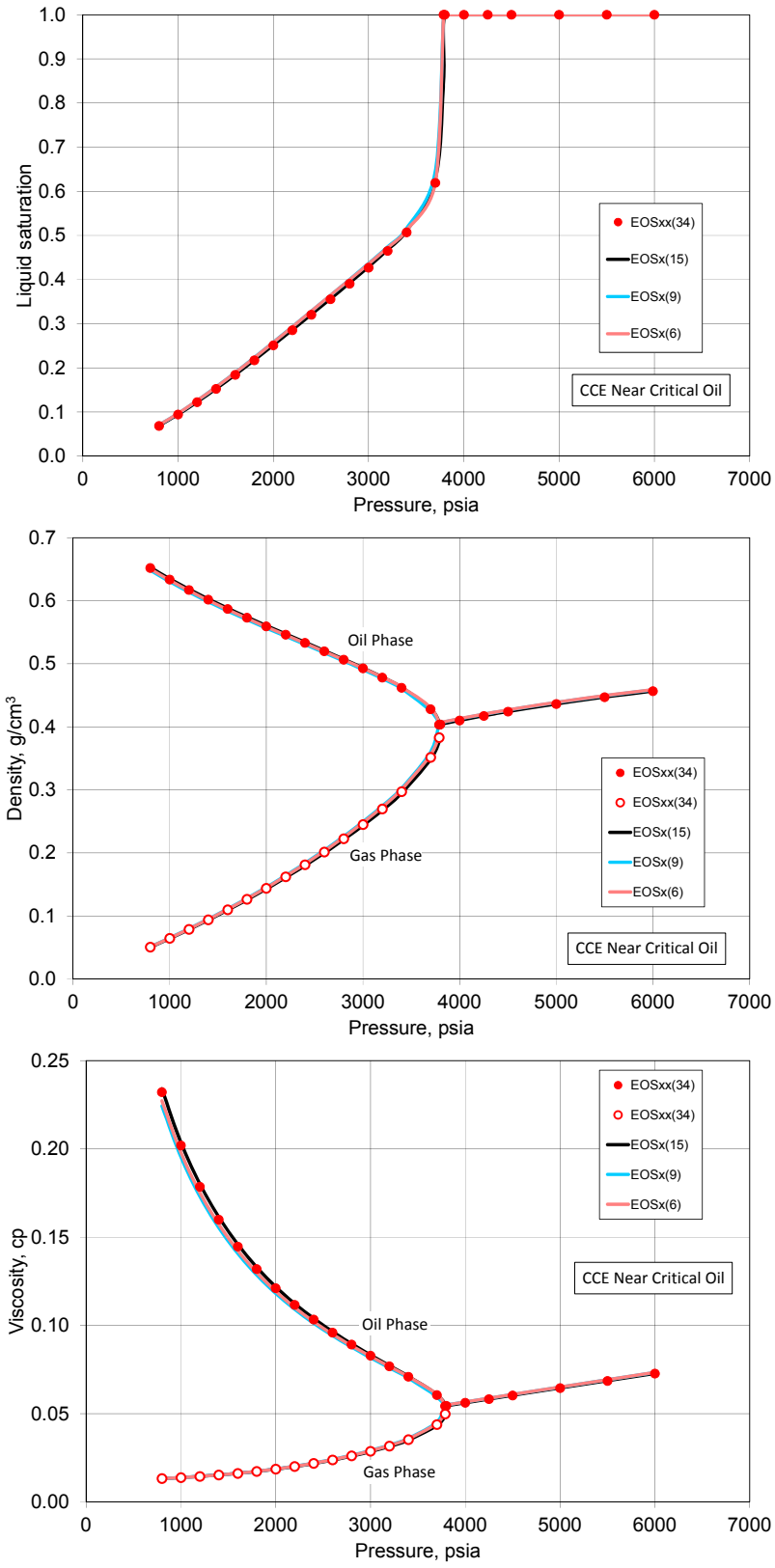

Fig. 10 – Near-Critical Oil EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #35,847 (best RMS); EOSx(6) scenario #45,284 (best RMS).

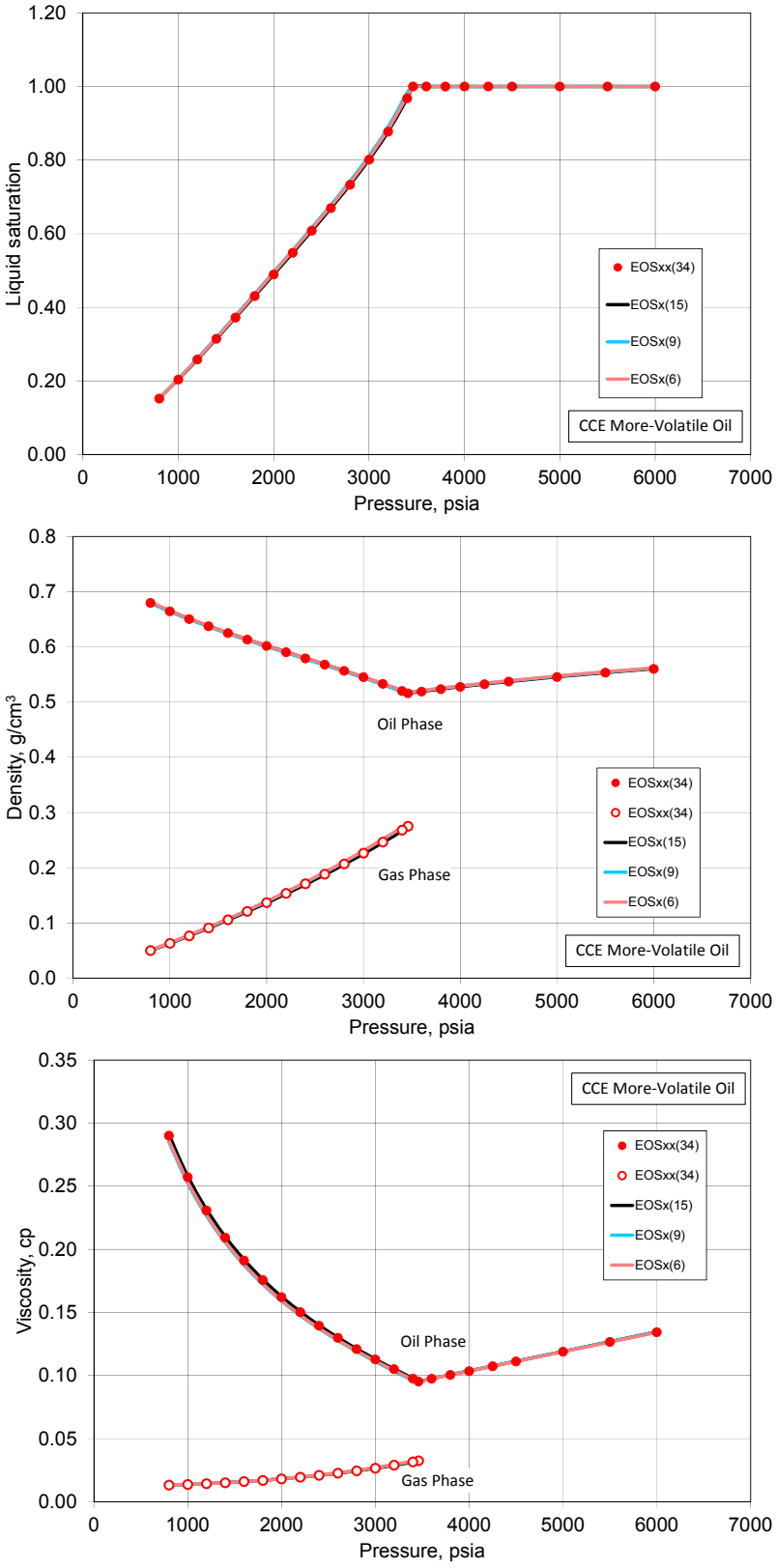

Fig. 11 – More-Volatile Oil EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

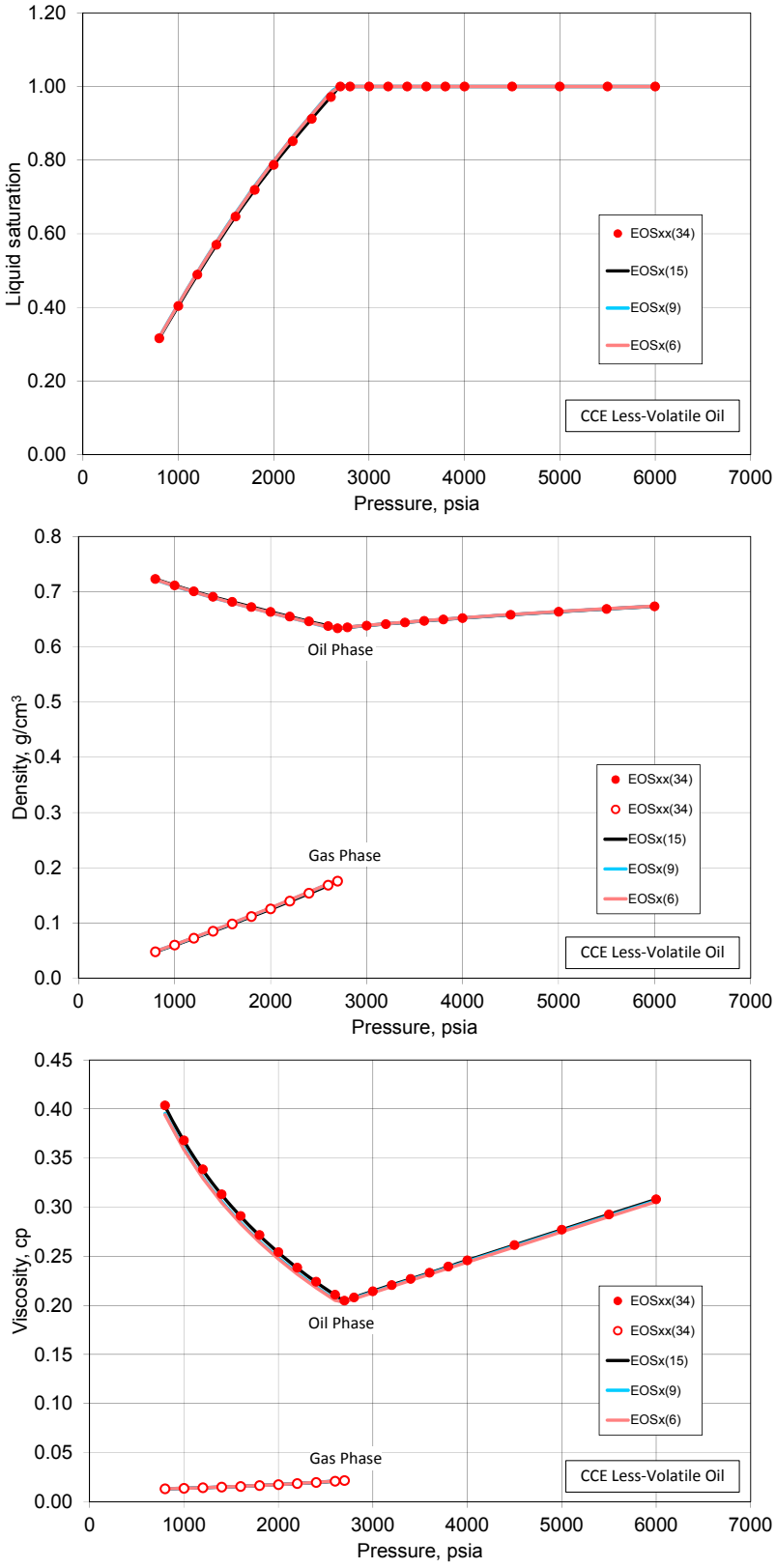

Fig. 12 – Less-Volatile Oil EOS calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

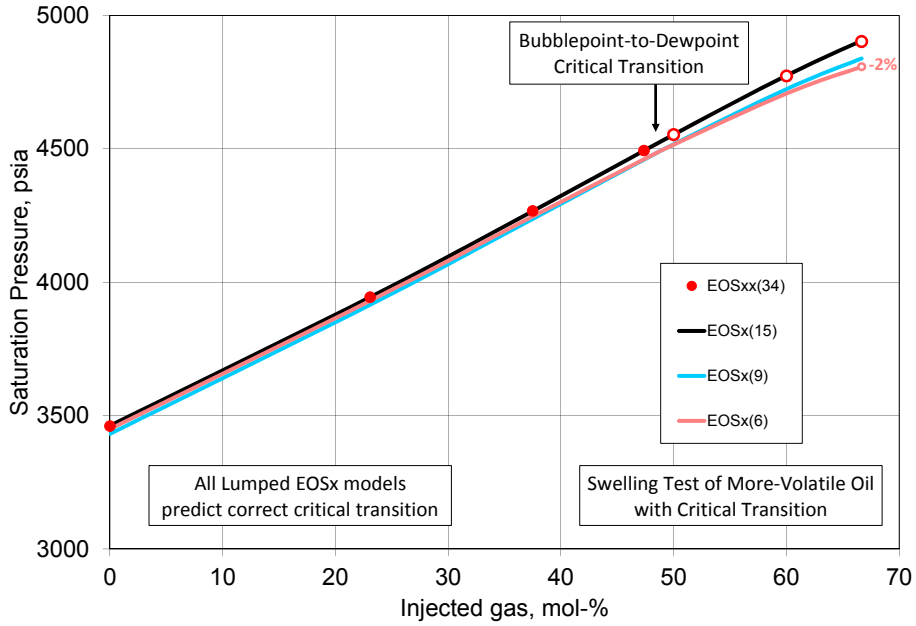

Fig. 13 – More-Volatile Oil swelling test calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #34,458 (best MMP); EOSx(6) scenario #47,959 (best MMP).

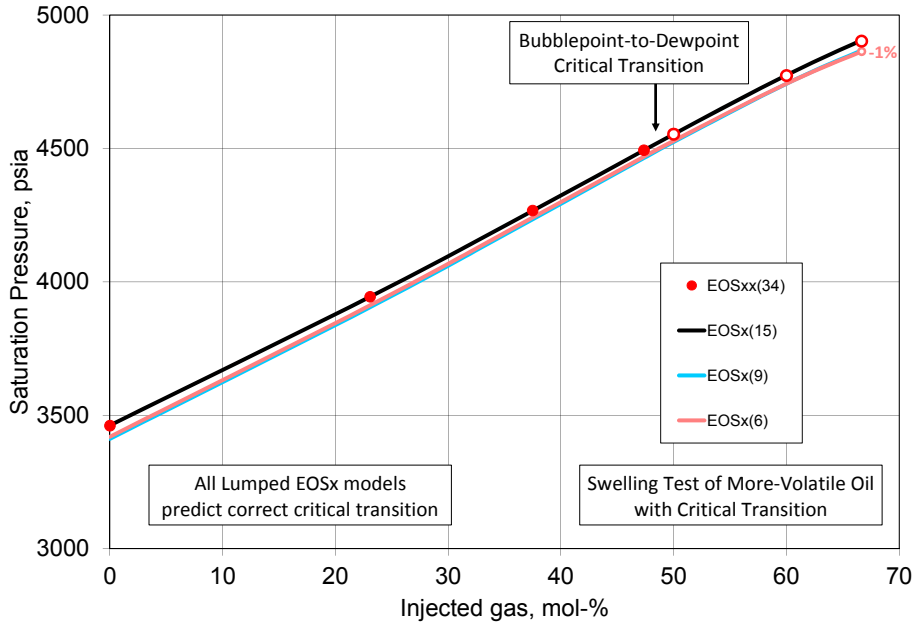

Fig. 14 – More-Volatile Oil swelling test calculations.
EOSx(15) scenario 4,587 (best RMS); EOSx(9) scenario #35,847 (best RMS); EOSx(6) scenario #45,284 (best RMS).