CT Scan and Neural Network Technology for Construction of Detailed Distribution of Residual Oil Saturation During Waterflooding

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Abstract

We present an integrated approach to imaging the progress of air displacement by spontaneous imbibition of oil into sandstone. We combine Computerized Tomography (CT) scanning and neural network image processing. The main aspects of our approach are I) visualization of the distribution of oil and air saturation by CT, II) interpretation of CT scans using neural networks, and III) reconstruction of 3-D images of oil saturation from the CT scans with a neural network model. The neural networks developed here construct 3-D images of fluid distribution at any time and/or location within the core. One neural network model interpolates between the CT images for a given position at different time levels and extrapolates beyond the interval of time during which the images were collected. Likewise, the network interpolates spatially between images at a given time. After interpolation and extrapolation, other network models have been developed to reconstruct the three-dimensional distribution of oil in the core. Excellent agreement between the actual images and the neural network predictions is found.

Introduction

An increasing global demand for energy and simultaneous depletion of conventional hydrocarbon reserves impose a formidable challenge for efficient recovery from nonconventional rock systems, such as naturally fractured reservoirs. Fractured petroleum reservoirs provide over 20% of the world oil reserves [1]. Examples of prolific fractured reservoirs are: the Monterey Shales in California (estimated tens of billions of barrels of oil-in-place); the California Diatomites (estimated fifteen billion barrels of oil-in-place); the West Texas Carbonates; the North Sea Chalks; and the Asmari Limestones in Iran.

Hydrocarbon recovery from naturally fractured reservoirs is not yet fully understood. This is mainly due to the lack of a complete understanding of multiphase flow through fractured porous media. Two- or three-phase flow in a fractured reservoir depends on the combined nonlinear effects of hydraulic connectivity and physiochemical properties of fractures, relative permeabilities to multiphase flow in the fractures, rock-matrix nature, matrix block size, capillary forces and fracture closure stress. The nonlinear interplay of all these factors determines the ultimate hydrocarbon recovery from fractured reservoirs. In contrast, most of the published data have been produced in controlled experiments that have focused on one or more of the above factors considered in isolation. These data are then upscaled in numerical simulators to model the coupled nonlinear behavior of fractured reservoirs. As a result, current numerical simulation models of fractured reservoirs lack firm predictive capability and must be tuned for each field case with the available data.

Thus, it might be helpful to undertake a systematic experimental and theoretical study of joint effects of all the factors governing multiphase fluid flow in a fractured porous rock. Of course, such a study is beyond the scope of this paper. Nevertheless, we have undertaken a study to evaluate the influence of four major factors on hydrocarbon recovery. These are: fracture configuration, rock-matrix block size, wettability characteristics of the rock, and fluid flow rates. This paper reports our progress on a scanning study of spontaneous imbibition of a hydrocarbon (kerosene) into a single air-filled block of rock matrix (Berea sandstone). Our experiments are a preamble to a more difficult study of the most important production mechanism in fractured reservoirs during
waterflooding, i.e., counter-current imbibition of water to displace oil and gas from the matrix. Here, we want to understand the pattern of imbibition from the distribution of fluid saturations and to design a neural network model of in-situ fluid saturations obtained directly from a CT scanner. The model is then used to generate three-dimensional time-lapse images of kerosene imbibition. Finally, we intend to incorporate the experimental results into our integrated-finite difference simulator, MN2NOTS (Multiphase Multicomponent Non Isothermal Organics Transport Simulator [2]), to allow for a more realistic simulation of multiphase flow through fractures. The mathematical formulation of MN2NOTS does not rely on a global coordinate system; therefore, it naturally extends the method of Multiple Interacting Continua [3] for modeling flow in fractured media to multiphase and multicomponent systems.

In this project, we use high resolution X-ray computerized tomography to obtain images of the cross-sectional distribution of kerosene and air in Berea sandstone cores as a function of time. Scans perpendicular to the axis of the core were made using a high resolution EMI 5005 (second generation) CT scanner. Each CT slice consists of a series of volume elements (voxels). Every voxel has its own characteristic attenuation, and can be mapped into a 2-D image matrix of picture elements (pixels). Using standard computer software, the 2-D fluid distributions at specific times and locations are visualized for each CT slice. CT is a fast, non-destructive imaging technique for determining in-situ fluid saturations and to design a neural network model of in-situ fluid saturations and to design a neural network model of in-situ fluid saturations obtained directly from a CT scanner. The model is then used to generate three-dimensional time-lapse images of kerosene imbibition. Finally, we intend to incorporate the experimental results into our integrated-finite difference simulator, MN2NOTS (Multiphase Multicomponent Non Isothermal Organics Transport Simulator [2]), to allow for a more realistic simulation of multiphase flow through fractures. The mathematical formulation of MN2NOTS does not rely on a global coordinate system; therefore, it naturally extends the method of Multiple Interacting Continua [3] for modeling flow in fractured media to multiphase and multicomponent systems.

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Neural networks are very useful in modeling nonlinear, complex, and multi-dimensional data and find wide application in analyzing experimental, industrial, and field data. Neural networks, unlike regression analysis, do not require specification of a structural relationship between the input and output data and they can be trained easily by using sufficient data from the system under study. In addition, neural networks have the ability to infer general rules and extract typical patterns from specific examples. These properties give the neural networks the ability to interpolate between typical patterns or data and generalize their learning in order to extrapolate to a region beyond their training domains.

**Principles of CT Imaging**

Various visualization methods have been used for fluid saturation determination during laboratory core flood experiments [4]. Some of the more common ones in use are transparent models [5], resistivity [6], microwave attenuation [7], NMR, MRI, X-ray, and gamma ray attenuation [8]. While most of these methods provide only average saturation and impose restrictions on experimental techniques, CT is a very fast and accurate technique with few restrictions on experimental conditions and offers fine spatial resolution [9]. Earlier investigators [10-16] have illustrated the importance of computerized X-ray tomography as a powerful tool for petroleum industry researchers.

To obtain a CT slice of an object, an X-ray source is collimated to provide a thin beam which is received by an array of crystal detectors. X-ray photons which strike these crystals cause them to fluoresce with an intensity proportional to the number of photons received. When a body is placed in the beam between the source and detector array, only those photons that are not absorbed by the body reach the detectors. Fig. 1a illustrates the principles of X-ray tomography. The values attained when the detectors are read represent the beam attenuation by an object placed in the path of the X-rays. The detectors are in a stationary array surrounding the object. The X-ray beams are always directed through the object aperture as the source moves around it in a circular path. The detectors are read at small rotational intervals and the resulting data are stored in a computer. This rotational excursion is called a pass and the total data acquired during this pass are termed a slice. After all readings for a slice have been acquired and stored in a computer, a cross-sectional image or matrix of attenuation coefficients μ(x, y) is created. Radon [17] established the mathematical foundation for image reconstruction from projection data. The basic synthetic unit is the volume element or voxel. The CT slice is composed of many voxels, each with its own characteristic attenuation, which are displayed as a 2-D image matrix of picture elements (pixels), shown in Fig. 1a.

CT measures linear attenuation coefficients μ, which are defined by Beer’s law:

$$\frac{I}{I_0} = e^{-\mu \rho x} \quad \text{(1)}$$

where $I_0$ is the source X-ray intensity, $I$ is the intensity measured by the detectors, $\mu$ is the linear attenuation coefficient, $\rho$ is the density of the medium, $\mu/\rho$ is the linear mass attenuation coefficient, and $x$ is the thickness of the material. If several materials are placed in the path of the X-ray beams, Beer's law can be generalized as:

$$\frac{I}{I_0} = e^{-\sum_i \mu_i / \rho_i x_i} \quad \text{(2)}$$

where $i$ is the material considered. If the object contains a mixture of components, the overall mass attenuation coefficient of the mixture is given by:

$$\mu_{\text{mix}} = \sum_i \mu_i S_i \quad \text{(3)}$$

where $S_i$ is the saturation of the phase $i$, i.e., $S_i$ is the volume...
fraction of component $i$ such as water, oil or gas.

Different mechanisms are involved in the adsorption of X-rays. The relative importance of these mechanisms depends on the energy level of the incident X-rays. In general, $\mu$ depends on both electron density, $p$, and atomic number, $Z$. If the energy is above 100 keV, $\mu$ depends mostly on the electron density (Compton scattering). For energy below 100 keV, photo-electric adsorption is the main mechanism, depending mostly on the atomic number $Z$ of the material studied. Thus,

$$\mu = \rho (a + b Z^{3.8}/E^{3.2})$$

(4)

where $a$ is the Klein-Nishira coefficient, $\rho$ is the electron density, $E$ is the energy level in keV, $Z$ is the atomic number, and $b$ is a constant with a value of $9.8 \times 10^{-4} \text{ keV}^{-2}$. Some conclusions that can be drawn from Eq. (4) are, I) heavier elements will attenuate more than the lighter ones, II) the coefficient of adsorption, $\mu$, for a given material changes with the energy level of the source and this change depends mostly on the atomic number of the element considered, and III) by measuring adsorption at two or more energy levels, one can obtain two independent measurements. This will help in solution of three phase problems as discussed in the Saturation Determination section.

Since it is impractical to deal with the X-ray attenuation coefficient, $\mu$, a new scale is defined based on the international standard unit of Hounsfield (H or CT number). On this scale, water has a value of zero and air has a value of -1000. Hence, each CT unit represents about a 0.1% change in the attenuation coefficient. Equation (5) defines the CT number

$$CT = \frac{\mu_x - \mu_{\text{water}}}{\mu_{\text{water}}} \times 1000$$

(5)

where $\mu_x$ is the calculated X-ray attenuation coefficient. In most CT scanners, the range of CT unit varies from -1000, representing air, to 4000, representing very dense materials. Reservoir rocks typically fall in the range of 1000 to 2000 on this scale.

**Saturation Determination**

In order to obtain fluid saturations, Eq. (1) can be written as:

$$P_f = \frac{\rho \mu \mu (1 - \phi) + \phi \mu \mu \rho (1 - \phi)}{\mu \mu + \mu \mu}$$

(7)

where $\rho$ is the bulk density of the system, $\mu$ is adsorption coefficient of kerosene, $\rho$ is the density of kerosene, $\mu$ is the adsorption coefficient of air, and $\rho$ is the density of air. From the measurement of an evacuated core, $\mu \rho \mu \rho (1 - \phi)$ is obtained. With $\mu$ and $\mu$ known, there are two equations with two unknowns:

$$\mu = \mu_k S_k + \mu_a S_a$$

(8)

where $S_k$ and $S_a$ are the saturation of kerosene and air respectively. Also,

$$S_k + S_a = 1$$

(9)

For three phase saturation (water-kerosene-air system), since there are three unknowns, an additional, independent measurement is required. This is done by scanning at a different energy level. The system of equations for three phase saturation determination are given by

$$\mu_1 = \mu_k S_k + \mu_w S_w + \mu a S_a$$

(10)

at energy level 1 (100 keV), and

$$\mu_2 = \mu_k S_k + \mu_w S_w + \mu a S_a$$

(11)

at energy level 2 (>100 keV). Finally,

$$S_k + S_w + S_a = 1$$

(12)

By scanning a fully kerosene saturated core, a fully water saturated core, and a fully air saturated core, $S_k$, $S_w$, and $S_a$ can be obtained.

**Neural Networks**

Imaging the process of spontaneous imbition in a Berea core using CT scanning methods has many limitations. One such limitation is the number of slices that can be obtained in space and time. For this study, only 4 sections perpendicular to the core axis were scanned at 20 mm separation and at only a few time intervals. In order to obtain fluid saturation distribution in space and time throughout the core, a neural network model was developed to interpolate between the CT images for a given position versus time and to extrapolate beyond the interval of time during which the images were collected. In this paper, only multi-layer perceptron networks with a back-propagation learning algorithm were used.

Historically, the development of neural networks followed the philosophy of emulating the brain. Many engineers and
scientists believed that if the functions of the brain could be emulated, many of the problems which are difficult and seem insoluble by traditional methods could be solved. During the last decade, a great number of neural network software packages and tools were developed. It is important to mention that the new interest in neural networks is due, in part, to advances in computer technology which have made it possible to bring together a large number of nodes and massive interconnections of simple neurons, much like the human brain. However, developing a proper neural network model that is an accurate representation of the process of interest still requires a combination of art, science, and technology.

During the past several years, successful applications of neural networks to solve complex problems have increased exponentially. Considerable attention has been devoted to the use of neural networks as an alternative approach to interpolation and extrapolation, pattern recognition [18], statistical, and mathematical modeling. For example, back-propagation neural networks [19] were used to develop process models as substitutes for complicated empirical and mathematical models [20]. These models can be used as an alternative to statistical and time series analysis. Neural network analysis, unlike regression, does not require specification of structural relationships between the input and output data. However, identification using neural networks is more useful when large amounts of data are available. Once the networks are trained using sufficient information, they achieve excellent predictive capability and show excellent generalization performance. Neural networks may be trained to analyze, predict, and optimize waste management, electrochemical, reservoir, and chemical processes [21]. Self organization maps, such as Kohonen networks [22], are used to classify different patterns of processes. Auto associated networks, such as Hopfield networks [23], are also used in pattern recognition.

Multi-layer perceptron networks with a back-propagation learning algorithm are perhaps the most widely used for process modeling, identification, pattern recognition, and pattern classification. The typical network has an input layer, where data are presented to the network, an output layer, which holds the response of the network to a given input, and at least one hidden layer, which connects the input layer to the output layer. There is no theoretical limit on the number of hidden layers, but typically there will be one. Each layer is fully connected to the succeeding layer with corresponding weights. The values of the weights represent the current state of knowledge of the network. These weights are adjusted to improve the network performance. They are either determined via an off-line algorithm such as the back-propagation algorithm [24], or adjusted on-line via a learning process [20, 25].

**Experimental Studies**

An EMI 5005 (second generation) CT scanner at Stanford University was used in this study. Fig. 1b displays the scanner components. The scanner consists of a mainframe, rotational elements, and scanner electronics. The mainframe houses the X-ray source, detector array, and beam shaping elements. The scanner assembly consists of a support table for positioning the core. The generator group is responsible for generating the X-rays. A combined Viewer/Operator Console consists of a video console, an interactive keyboard for viewing, initiating image generation, and for image manipulation. The computation unit performs sequencing, interprets instructions, and executes them. The Video Generator accepts image information in digital form and converts it to the image seen on the viewing monitors. A Disk Drive stores these images. The Magnetic Tape Unit records images from the Disk Drive for long term storage of information.

The cores were scanned at an energy level of 140 keV and a field size of 13 cm. A small field of scan was used to obtain better spatial resolution, as the number of pixels available remain constant. Slice thickness was made as small as possible, i.e., 3 mm (it varies from 1-10 mm), in order to minimize errors and maximize resolution. Greater slice thickness results in greater measurement error. Also a scan angle of 398° was used as it produces the highest resolution due to an overscan of 38°.

The core holder/experimental cell was constructed from acrylic which is relatively X-ray transparent. A schematic of the experimental setup is shown in Fig. 2a. The core holder, 6.4 cm in diameter and 21 cm long, is provided with two end caps for fluids to flow in and out of the core holder. The inlet endcap is connected to a fluid tank through a rubber tube. A control valve attached to the tank controls the flow of fluid from tank to coreholder. The outlet endcap is connected to a measuring vessel. The axis of the cylindrical Berea sandstone core was aligned with the axis of the core holder so that the core was exposed to uniform fluid saturation on all the sides. The sandstone used for this study has a porosity of 22% and a permeability of 300 md. Kerosene used as the hydrocarbon for this study has a specific gravity of 0.80 and viscosity of 1.152 cp at 21°C. Kerosene-air surface tension is 23-32 dynes/cm at 21°C.

Core preparation prior to the start of the experiment involved firing the cores for 24 hours at 750°C. This was done to remove effects of clay swelling and migration from the imbibition process. The cores were initially at 1 atm pressure and saturated with air. At the onset of the experiment, the first images were scanned at four different axial locations within the air-filled core holder in a single run to obtain dry core CT values (CTdry). Four 3 mm thick axial scans were taken at 20 mm spacing. Location of the four faces with reference to the two end faces are shown in Fig. 2b. Later, the valve attached to the fluid tank was opened and kerosene filled the core holder until the whole core was uniformly submerged in kerosene. X-ray scanning was done along the core at the same locations to
obtain CT values ($CT_{exp}$) at times of 1, 5, 10, 15, 25, 35, 50 minutes, and at every 60 minutes for next 240 minutes after the core was exposed to kerosene to obtain temporal distribution of kerosene within the core. The scanning procedure determined the average saturation of the core sample at each location. Scanning was also conducted at 24 hours and 48 hours after the start of kerosene imbibition. Weight of the core was measured at the beginning and end of the experiment for mass-balance calculations. Scanning was performed at the same axial locations in all the runs to obtain the spatial distribution of kerosene.

**Results**

For brevity, we only report images obtained at 5, 10, 15, and 25 minutes after the start of kerosene imbibition. This is because most of the observable dynamics of kerosene imbibition were found to have occurred in first 15 minutes of the experiment. An analysis of images obtained at later periods showed only very small changes in the overall kerosene saturation of the core.

For calculating kerosene saturation in any slice of the core, Eq. (13) is applied to each pixel of the slice:

$$S_{kerosene} = \frac{CT_{kerosene} - CT_{exp}}{CT_{kerosene} - CT_{dry}}$$

and

$$S_{air} = 1 - S_{kerosene}$$

$CT_{kerosene}$ is the CT value for a fully kerosene saturated core. In this study, slices obtained from X-ray scanning after 48 hours of kerosene imbibition were used to determine the fully kerosene saturated core CT values. After 48 hours of kerosene imbibition, the core appeared to have reached irreducible air saturation, as no further changes were noticed in the CT values. From mass-balance calculations, the final kerosene saturation in the core is 80%. Thus to obtain accurate saturation values, values obtained from Eq. (13) were multiplied by a factor of 0.8. We are currently developing a better method of rescaling the images directly from the raw X-ray attenuation data.

There were also problems using the $CT_{exp}$ values obtained from scanning the core surrounded only by air. All the other images were scanned after filling the core holder with kerosene. Differences in densities of the surrounding media cause differences in the absolute values of attenuation coefficient $\mu$ inside the core. For obtaining the $CT_{dry}$ values to be used in Eq. (13), inner dry portions of the slices obtained after 1 minute of kerosene imbibition were used. To obtain kerosene saturation profiles, average kerosene saturation was calculated in annular rings of each slice, within circles at increasing radii, and finally in sectors. This averaging procedure is illustrated in Fig. 2c.

**Fig. 3** shows a series of images obtained after the kerosene has imbibed into the core for 5, 10, 15, and 25 minutes at the four axial sections of the core. The images represent the distribution of kerosene saturation inside the core. In all these images, white represents zero kerosene saturation, and black represents the maximum kerosene saturation or 100%. Figs. a-1 through d-1 are the images of Berea core after 5, 10, 15 and 25 minutes of kerosene imbibition at section 1, located 2 mm from the core face. In these images, there is a clear lack of an oil front, because axial flow dominates over radial flow in this section. Thus at all times, the whole slice appears uniformly saturated. There is the possibility of a kerosene front at very early times. However, nothing conclusive can be said from the information available. Also, kerosene saturation increases uniformly but consistently with time from image a-1 to d-1. Image d-1 appears to 80% oil saturated.

Berea slices obtained at section 2, 22 mm away from the left core face, are shown in images a-2 through d-2. Due to location of the slices far away from the core faces, radial flow dominates in this section. This is seen as a clear front observed at early times and represented by a dark annulus at the edge of the slice. Image a-2 obtained after 5 minutes of kerosene imbibition shows a very sharp front, that gradually changes to a more diffuse front in image b-2, and finally disperses after 15 minutes as seen in images c-2 and d-2. In image a-2, kerosene is imbibing uniformly into the core from all the sides and imbibes radially into the sample as a sharp front. Analysis of the saturation-matrix shows that the front is dispersed over 3-4 mm range. In image b-2, the kerosene saturation annulus appears to be moving radially inside the core and has thickened as compared to image a-2. There is also a gradual increase in the kerosene saturation towards the core edges as would be expected. Image c-2 shows the kerosene saturation in Berea core after 15 minutes of imbibition. The kerosene front has dispersed by this time. High kerosene saturation values in the center of the section show that the kerosene has reached the center of the core. The kerosene saturation distribution after 25 minutes of imbibition is shown in image d-2. The image d-2 shows that approximately 80% kerosene saturation is obtained uniformly throughout the core and stays constant.

Again in section 3, 25 mm from the right face of the core, an imbibition pattern in time similar to that of section 2 is observed. Radial flow dominates and hence changes in kerosene concentration are observed radially with time. A sharp kerosene front in image a-3 changes to a slightly less sharp front in image b-3 and finally disperses in images c-3 and d-3.

A similar kerosene imbibition history is seen in images obtained at section 4, 5 mm from the right face of the core. Section 4, however, is quite different from section 1, especially at the early stages of the imbibition process. This is also due to a predominance of radial flow. A clear pattern can
be seen from a-2 to a-4, and b-2 to b-4. A sharp front exists in the early part of the imbibition, then it diffuses slightly and finally disappears after 15 minutes, as shown in Figs. 3c-4 and 3d-4. However, the distribution of kerosene saturation in section 4 differs from those in sections 2 and 3. Around 10 minutes of imbibition, axial effects combine with radial flow. This cannot be seen in images 3c-4 and 3d-4 as the core reaches uniform saturation distribution and the axial flow effect is masked. In summary, the behavior of section 4 in the early stages of the imbibition process is similar to the behavior seen in section 2 and 3. In the late stages of imbibition, it is a combination of the behaviors of sections 1, 2, and 3.

To illustrate the imbibition pattern of kerosene in Berea sandstone more clearly, saturation profiles along the diameter of the core at each section are presented in Fig. 4. Figures 4a-1 through 4d-1 show kerosene saturation profiles obtained in section 1 at 5, 10, 15 and 25 minutes. In agreement with the images of Fig. 3, the saturation profiles 4a-1 to 4d indicate that axial flow dominates. A consistent increase in kerosene saturation is observed as we go from Fig. 4a-1 to 4d-1. An analysis of Figs. 4a-2 to 4d-2, representing kerosene saturation profiles with time at section 2, show the progression of a very sharp radial front extending over a range of 3-4 pixels or 1.1 to 1.5 mm. The kerosene front width increases to 7-10 pixels or 2.6 to 3.7 mm at 10 minutes in Fig. 4b-2, and finally disappears after 15 and 25 minutes in Figures 4c-2 and 4d-2.

The history of average kerosene saturation in a circular annulus of the core at different radii is shown in Fig. 5. Here, average annular kerosene saturation is plotted as a function of radial distance and time. It shows the movement of a kerosene front, the knowledge of which is extremely important for interpolation between the images. In Fig. 5a through 5d, white shading represents zero kerosene saturation and black shading represents 100% kerosene saturation. Shades of gray represent intermediate saturations. Trends found in Figs. 5a through 5d are similar to those shown earlier in Figs. 3 and 4. At section 1 in Fig. 5a, 2 mm from the left face, at times 5-15 minutes, no change in kerosene saturation occurs radially due to predominant axial flow. Uniform increases in kerosene saturation between 5 and 15 minutes is observed. After 15 minutes, no further change in kerosene saturation occurs either radially or with time. Figs. 5b, 5c, and 5d at sections 2, 3, and 4, respectively, exhibit a similar trend in kerosene imbibition and a trend similar to that seen in Figs. 3 and 4 in sections 2, 3, and 4. Kerosene imbibition at 5 minutes occurs only at a radial distance of 20 mm, i.e., near the edge of the core. Kerosene first reaches the center of the core at 12 minutes. Also, a sharp kerosene front is seen during the first 15 minutes, after which the front disappears.

In order to smooth the kerosene saturation distribution, average kerosene saturation within a circle is presented as a function of time and radial distance in Fig. 6. The purpose of these plots is to show minute changes in the kerosene saturation fronts. Kerosene imbibition patterns observed earlier in Figs. 3, 4 and 5 are exactly similar to those shown in Fig. 6 at all the four sections. A lack of front is seen in Fig. 6a at section 1, and sharp fronts in Figures 6b, 6c, and 6d at sections 2, 3, and 4 until 12 minutes. Beyond 15 minutes, the kerosene front becomes non-existent.

Fig. 7 is a plot of percent kerosene saturation versus axial distance from the closest core face at different times. In Fig. 7 at section 1, the core is saturated. Kerosene saturations range from 45% to 82% after 5 to 25 minutes of kerosene imbibition.

Plots of average kerosene saturation in a specific annular ring versus time is shown in Fig. 8-1a through 8-1d. A nearly uniform kerosene saturation is observed in Fig. 8-1a, representing section 1, at all times. Kerosene saturations increase from the edge to the center of the core at 5, 10, and 15 minutes. The change in saturation with radial distance at 25 minutes is very small indicating that the core has reached a steady state. Figures 8-1b through 8-1d show a very sharp front at 5 minutes that changes to more diffuse front at 10 minutes and no front at times 15 minutes and 25 minutes. Similar trends can be observed in Figs. 8-1c and 8-1d, i.e., sections 2 and 3, respectively, and similar to that in Fig. 8-1d, i.e., section 4 at earlier times. However, the trend is different from Fig. 8-1d at later times and is a combination of sections 1, 2, and 3 at times 15 and 25 minutes.

Average oil saturation within a specific annulus as a function of radial distance versus time is plotted in Fig. 8-2. A smaller profile band width in Fig. 8-2a, representing section 1, shows uniform imbibition all throughout the core which is due to the axial flow pattern at section 1, 2 mm from the left face of the core. Figs. 8-2b through 8-2d representing sections 2, 3, and 4, respectively, show a wide profile band width indicating that a radial flow pattern is more prevalent in these sections as there is a large change in saturation with radial distance. However, all the profiles converge to a very narrow region beyond 15 minutes as most of the imbibition process ends before 15 minutes. Figures 8-2b and 8-2c have a similar width as compared to Fig. 8-2d at earlier times. At later times, i.e., after 15 minutes, profile width pattern in Fig. 8-2d becomes a combination of those in Figures 8-2b and 8-2c.

**Design of Neural Network Models**

The network model for axial mapping has two nodes in the input layer representing the axial coordinate and elapsed time, both scaled uniformly between 0 and 1. It has 3 nodes in the hidden layer with nonlinear transfer function, and one node in the output layer predicting the total average saturation in each circular cross section, and also with nonlinear transfer function. The data in Fig. 7 were used to train the network. Due to the limited volume of data available, all the data were used in the training. The model was trained until the prediction suffered upon continued learning. Figs. 7a and 7b show the performance of the network model for predicting the average oil saturation as a function of time and axial position. The
results show perfect mapping and excellent prediction of the saturation for the training data set. Even though only 4 images were available in the axial direction, the model had excellent performance. Therefore, better performance with higher accuracy and confidence level will be expected if more axial information is introduced into the network model.

To model the radial behavior presented in Figs. 8-1a to 8-1d, and Figs. 8-2a to 8-2d, a different neural network was designed. This network has three nodes in the input layer representing the axial coordinate, radial coordinate, and elapsed time, all scaled uniformly between 0 and 1. It has 15 nodes in the hidden layer with nonlinear transfer function, and one node in the output layer representing the average saturation in a sector of 2 pixels in the radial direction and 10 degrees in the azimuthal direction. In addition, the axial images were also included into the interpolation model. In this study, images a-2, c-2, b-3, and b-4 in conjunction with the network model were used to reconstruct the image 9d. Comparing image 9a and 9d, one can see that the model reconstructed the actual image almost perfectly. The maximum expected error based on this technique is less than 5%.

Conclusions
Kerosene imbibition in a dry Berea core was successfully imaged using CT scans and correct fluid saturations were computed. Images scanned in the interior of the core show a sharp front propagating radially at short times. The front gradually diffuses and disperses totally after 15 minutes, as the entire cross-section fills with kerosene. Spontaneous imbibition of kerosene in an air-saturated Berea core with diameter 5.46 cm and length 6.7 cm is a comparatively fast process with most of the observable dynamics ending in 15 minutes. A relatively fast and accurate technique for imaging fluid flow in a porous medium, such as CT scanning, is quite adequate for tracking kerosene imbibition and for measuring the distribution of in-situ fluid saturations. However, CT experiments must be carefully designed to avoid excessive experimental error in a limited number of images that can be obtained in time and space. As most of the observable dynamics of kerosene imbibition were over in 15 minutes, it was imperative to obtain images at several short time intervals. Also, it is important to scan all the images with a similar medium surrounding the core. A core imaged in surrounding media of different densities has different absolute values of attenuation coefficient, $\mu$. CT values of such images lead to improper determination of saturations.

To train the neural networks for proper prediction of spatial and temporal distribution of fluids, a large number of data points are needed. Due to scanner limitations (heating up of cathode-ray tube), images could only be obtained at 4 time intervals during the first 15 minutes. Thus, data obtained from such experiments are in general quite insufficient for proper neural network modeling. Axial information was sparse and even though our network interpolated properly between the existing images we are uncertain as to its extrapolative quality at core ends. Fortunately, the homogeneous Berea sandstone core behaved predictably, and we obtained sufficient radial information to train the network.

Nomenclature

- $a$ = Klein-Nishira coefficient, (-)
- $b$ = constant in Eq. (4), $9.8 \times 10^{-14}$, mL/$t^2$, keV
- $E$ = energy level, mL/$t^2$, keV
- $I$ = detected X-ray intensity, $l/t$, counts/min
- $I_o$ = incident X-ray intensity, $l/t$, counts/min

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\( \phi \) = porosity, percentage
\( \rho \) = density, m/L^3, gm/cc
\( S_i \) = saturation of the phase i, \% PV
\( \mu \) = linear attenuation coefficient, L^1, cm\(^{-1}\)
\( x \) = thickness of material, L, mm
\( Z \) = atomic number

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References


CT SCAN AND NEURAL NETWORK TECHNOLOGY FOR CONSTRUCTION OF DETAILED DISTRIBUTION OF RESIDUAL OIL SATURATION

Fig. 1a-CT scanning process

Fig. 2a-Schematic of experimental setup

Fig. 1b-The scanner system

Fig. 2b- Schematic of sections scanned in the Berea core

Fig. 2c-Schematic of configurations considered for kerosene average saturation calculation
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Fig. 3-CT images of kerosene imbibition into Berea Sandstone core
Fig. 4: Kerosene saturation profile along the horizontal diameter of the core.
Fig. 5: Average oil saturation within a specific circular ring with a specific radius at different times.

Fig. 6: Average oil saturation within a specific circle with a specific radius at different times.

Fig. 7: Comparison between actual data and neural network prediction for average saturation in each section.
Fig. 8-1 Comparison between actual and neural network prediction for average oil saturation within a specific circular ring with a specific radius at different time.
Fig. 8-2 Comparison between actual and neural network prediction for average oil saturation within a specific circular ring with a specific radius at different time.
Fig. 9: Comparison between actual CT image with neural network prediction and linear interpolation.