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Distributed Multiphase Flow Metering Using Fiber Optic Sensing

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Abstract

Distributed Acoustic Sensing (DAS) technology has been used in an increasing number of applications in the petroleum industry. In this work we focus on distributed multiphase flow rate measurement. We develop a mathematical model that relates multiphase flow rates and two-phase flow patterns in the wellbore to the DAS data. This forward model consists of a series of analytical relationships between various physical parameters and allows for simulating DAS data efficiently based on various assumptions regarding the flow and wellbore. In the second part of the paper, we discuss an inverse modelling strategy to analyze DAS data to find distributed flow rates in the wellbore. The inverse model employs the wavelet transform and artificial neural networks to analyze DAS data in real time and calculate the flow rate and flow patterns in the wellbore.

Introduction

Distributed Acoustic Sensing (DAS) is a relatively new technology in the petroleum industry with many applications such as vertical seismic profiling (Mateeva et al. 2014), injection profiling (Xiao et al. 2014), and multiphase flow profile measurement throughout the wellbore (Finfer et al. 2014). Many more DAS applications are expected to emerge in the future.

In this paper we investigate using DAS to measure flow rates in the wellbore. DAS data and flow in the wellbore are related through multiple stages of physical relationships that depend on various parameters related to formation, wellbore, fluid flow, and optical fiber. Flow in the wellbore is typically turbulent, which can be challenging to model under multiphase flow conditions (Bakker 2004). Typically, one has to make several assumptions about the flow regime (e.g. bubbly, slug, annular, etc.), coupling between phases, and hydrodynamic effects (e.g., change in the shape of bubbles, collisions between bubbles, etc.). The frictions in turbulent flow and fluid-tubing interactions result in sound waves in the fluid and on the tubing. The fiber optic cable is attached to the tubing with clamps. Due to the mechanical coupling between the tubing and the fiber, the acoustic waves on the tubing directly impact the optical fiber, perturbing the optical signal in the fiber. The optical signal is processed to obtain the acoustic signal along the fiber.

Due to the several layers of physical relationships linking multiphase flow in the wellbore to the DAS data, DAS analysis offers an indirect measurement of the flow rate. The set of calculations starting with the flow rate and ending with DAS data is known as the forward problem (Tarantola 2005). Using DAS data to estimate flow rates is the inverse problem. The inverse problem and the forward problem are closely related.

DAS systems typically produce a large amount of data. The desired approach is to process data in the field in real time and extract physically meaningful and actionable aspects of the data that are actually needed to characterize the well and the reservoir. Consequently, it is crucial to develop efficient algorithms to analyze DAS data quickly and provide a real-time solution.

In the first part of the paper we develop a set of analytical relationships for the forward problem that relates multiphase flow in the wellbore to the DAS data. In the second part of the paper we discuss efficient solution strategies for the inverse problem using advanced signal processing and machine learning techniques.

Part I: Forward Model

In this section we study the relationship between two-phase turbulent flow in the wellbore and the resulting acoustic waves along tubing. Fig. 1 shows an overview of the mechanisms that relate the flow in the wellbore to the output of the DAS system. It should be noted that there are several sources that generate sound waves in the wellbore other than multiphase flow, such as electric submersible pumps, inflow control valves, gas lift valves, inflow of hydrocarbons through perforations, and leaks. The acoustic signals from these other sources do not necessarily carry information regarding the flow rates, yet they are picked up by the DAS sensors. Also, in turbulent flow various frictional forces result in swirling patterns and reversed currents that convect in the wellbore. These are called eddies and they carry important information related to the flow rate. The modeling we develop in this section only focuses on the acoustic signals generated by the flow.

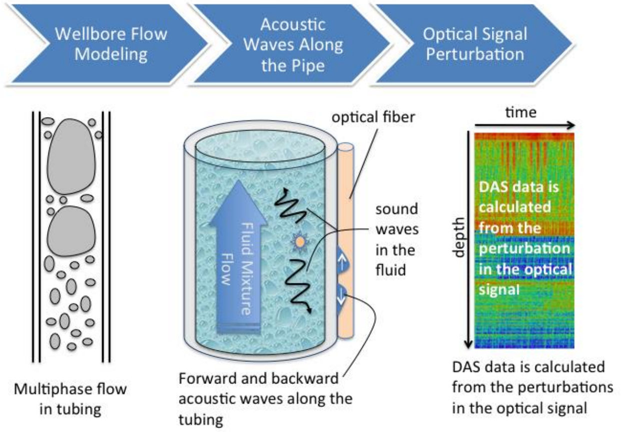

Fig. 1— DAS systems give an indirect measurement of the flow rate. There are several layers of physical relationships linking the flow in the wellbore to the DAS data.

There are large variations in pressure and temperature along the wellbore, which impact fluid properties, fluid velocities, and in-situ volume fractions of the phases. Certain flow patterns emerge as a consequence of deformable interfaces between the phases. Common flow patterns include bubbly flow, slug flow, churn flow, and annular flow. The dynamics of each pattern differ from each other and the patterns transition from one into another. Hasan and Kabir (2002) developed a mechanistic model to study the flow patterns and the pressure drop in the wellbore. According to this model, the generalized form of gas-volume fraction relationship can be written as (Hasan et al. 2007):

$$f_g = \frac{v_{sg}}{C_o v_m + v_\infty} \tag{1}$$

In Eq. 1 v_{sg} is the superficial velocity of the gas phase, v_m is the velocity of the mixture, C_o is a flow parameter corresponding to the ratio of the velocity at the center to the average velocity, and v_∞ is the bubble rise velocity. Liquid holdup can be calculated as:

$$f_L = 1 - f_g \tag{2}$$

Total pressure gradient in the wellbore is the sum of the static, friction, and kinetic components and is given by

$$-\frac{dp}{dz} = g\rho_m + \frac{f_m v_m^2 \rho_m}{2d} + \rho_m v_m \frac{dv_m}{dz} \tag{3}$$

The pressure profile in the wellbore can be calculated iteratively using Eq. 3. The details of this approach can be found in Hasan et al. (2007). In this approach, the single-phase formula is extended to include multiphase effects by using average parameters for the oil-gas mixture. The speed of sound in two-phase flow can also be modeled by using average parameters (Bukhamsin & Horne 2014; Unalmis 2015):

$$c_m = \left[\rho_m \left(\frac{f_L}{\rho_o c_o^2} + \frac{f_g}{\rho_g c_g^2}\right)\right]^{-1/2} \tag{4}$$

In Eq. 4, c_o and c_g are the speed of sound of oil and gas phases, respectively. c_m is the speed of sound in the oil-gas mixture not accounting for the impact of tubing. The average phase density is given by:

$$\rho_m = f_L \rho_o + f_g \rho_g \tag{5}$$

The speed of sound for oil can be calculated from:

$$c_o = \sqrt{\frac{K_o}{\rho_o}}, \tag{6}$$

where K_o is the bulk modulus of the oil phase. For the gas phase, the following relationship can be used (Smith & Clancy 2011):

$$c_g = \sqrt{c_r \left(\frac{RT}{M_r}\right)\left(Z + \rho_g \left(\frac{\partial Z}{\partial \rho_g}\right)_T\right)}, \tag{7}$$

where c_r is the real gas specific heat ratio, M_r is the molar weight of the gas, and Z is the compressibility factor. Eq. 6 and Eq. 7 are useful to understand the sensitivity of the speed of sound to temperature and pressure. In practice, the speed of sound can be characterized empirically in laboratory measurements for each phase.

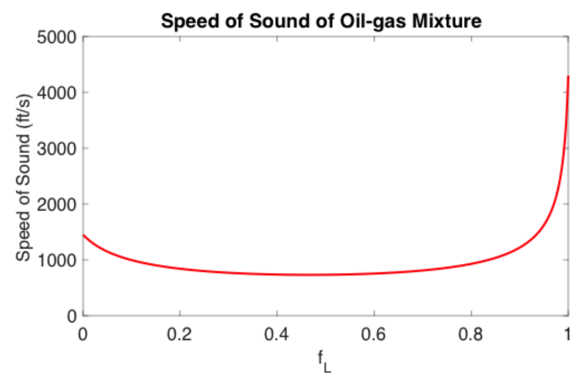

Fig. 2— Speed of sound as a function of liquid holdup based on Eq. 4. In this illustrative example the parameter values are ρ_o= 32 lbm/ft3, ρ_g=2.2 lbm/ft3, c_o= 4300 ft/s, and c_g= 1450 ft/s (adapted from Unalmis 2015).

As temperature and pressure vary throughout the wellbore the speed of sound can be calculated as a function of depth along with pressure profile calculation using the Hasan-Kabir iterative approach. As seen in Eq. 4, the speed of sound is sensitive to the compositional changes of the fluids throughout the wellbore. Fig. 2 shows an illustrative example that demonstrates the sensitivity of the speed of sound on compositional changes. For example, a sharp change in the speed of sound from 4000 ft/s to 2000 ft/s in oil-rich flow can be attributed to gas breakthrough (Unalmis 2015).

Acoustic Waves on Tubing: Once the speed of sound for the oil-gas mixture is found, we can calculate the acoustic waves generated on the tubing. Ocalan et al. (2016) studied acoustic wave propagation in a pipe filled with a stationary fluid and derived an analytical relationship that relates the acoustic wave traveling in the pipe to radial oscillation of the pipe wall. The discussion below is built on that study and accounts for the Doppler effect due to fluid flow and multiphase flow effects.

Consider a tubing filled with an oil-gas mixture. At a given point in the wellbore, the frictions within the fluid and between the fluid and the tubing generates acoustic waves, for which the governing equation is given as:

$$\frac{1}{c_m^2}\frac{\partial^2 p_p}{\partial t^2} = \nabla^2 p_p\,, \tag{8}$$

where p_p is the perturbation pressure in the fluid resulting from the generated sound. In general $p_p = p_p(r, \varphi, z, t)$. For simplicity, we can assume p_p is axisymmetric (no φ dependence), in which case the solution to the wave equation is given as:

$$p_p(r, \varphi, z, t) = p_{p,0}\, J_0(k_r r) e^{i(k_z z - \omega t)}, \tag{9}$$

where r is the radial coordinate, z is the axial coordinate (positive in the direction of the flow), k_r and k_z are wavenumbers in the radial and axial directions, J_0 is the Bessel function of the first kind, and ω is the angular frequency of the wave. The sound wave generated in the flow includes many frequency components.

Using momentum balance equations in the tubing, tubing displacement resulting from acoustic waves in the fluid can be described as follows (Ocalan et al. 2016):

$$\Delta r = \frac{p_{p,0} d^2 J_0(k_r d/2)}{4Eh}, \tag{10}$$

where Δr is the radial perturbation on the tubing, d is the diameter of the tubing, E is Young's modulus, and h is the thickness of the tubing.

We can then calculate the speed of the acoustic wave on the tubing:

$$c_t = c_m \left(1 + \frac{d\rho_m c_m^2}{Eh}\right)^{-1/2}, \tag{11}$$

where c_t corresponds to the speed of sound on tubing filled with a stationary fluid and c_m is the bulk speed of sound in unconstrained fluid. Because of the flow in the wellbore, backward and forward propagating waves on the tubing will have different velocities due to the Doppler shift:

$$v_+ = v_m + c_t, \tag{12}$$

$$v_- = v_m - c_t \tag{13}$$

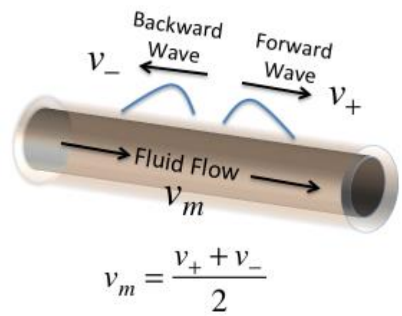

Fig. 3— Fluid flow rate can be calculated from speed of sound measurements.

The speed of sound on the tubing is different than the bulk value c_m as a result of acoustic coupling between the tubing and the fluid. Per Eq. 11, the relation between the speed of sound in bulk fluid and wave velocity on the tubing depends on tubing diameter d, Young's modulus E, and tubing thickness h. In DAS applications, multiphase flow rates are estimated by first estimating the speed of sound of the forward (v_+) and backward (v_-) waves. As shown in Fig. 3, one can estimate the total flow velocity v_m and stationary speed of sound c_t from Eq. 12 and Eq. 13. Lastly, from Eq. 4 liquid holdup can be estimated. Note that, if Eq. 11 is not taken into account to relate the speed of sound in the fluid to the speed of sound on the tubing, the measured multiphase flow rates can deviate from the actual value.

Speed of sound based flow rate measurements can have uncertainty issues for liquid flow rates because usually $c_m \gg v_m$ for oil flow. Considering the right hand sides of Eq. 12 and Eq. 13, the uncertainty in the speed of sound may dominate the flow velocity (Unalmis 2015). In multiphase flow, to estimate the holdup using Eq. 4, one needs to know the oil and gas densities. Hence additional uncertainty comes from variation in the density of oil during production. One way to mitigate the uncertainty in flow rate associated with speed of sound is to utilize eddies for flow rate estimation.

Optical Fiber Sensors: Optical fibers are most commonly used for transmitting high-speed optical data signals over long distances with very low loss. Over the last two decades optical fiber systems have been utilized increasingly in sensing applications as well (Lee 2003). In DAS applications the entire fiber acts as a sensor: The optical phase of the light is modulated as the pressure fluctuates along the fiber due to acoustic waves. An optical detection system connected to the fiber uses a series of optical signal processing techniques to extract the phase information accurately, which is sampled, calibrated, and stored as raw DAS data.

Part II: Inverse Model

In this section, we will discuss a DAS analysis strategy to estimate the flow patterns in the wellbore and characterize multiphase flow. In the literature, DAS data processing has been the topic of several publications (Johannessen et al. 2012; Da Silva et al. 2012; Xiao et al. 2014; Bukhamsin & Horne 2014).

Conventionally, DAS data processing starts with using two-dimensional Fourier transform on a segment of the depth-time DAS data to obtain a frequency-wavenumber (ω-k) representation (Fig. 4). The V-shaped maxima of the Fourier coefficients on the ω-k plot are used to estimate the speed of the forward and backward propagating sound waves. Once the speed of sound is calculated, multiphase flow rates can be calculated from Eq. 11 – Eq. 13.

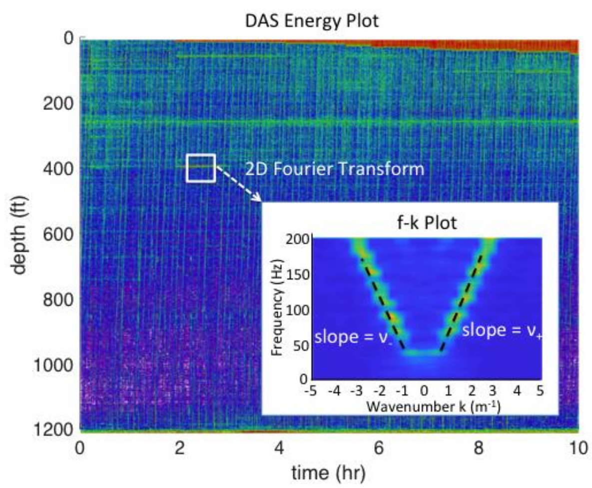

Fig. 4— 2D Fourier Transform of sections of the DAS data gives the frequency-wavenumber plot (inset). The slope of the maxima of Fourier coefficients gives v+ and v-.

Finding the speed of sound as a function of depth and time requires applying the procedure in Fig. 4 several times. This procedure can be slow and computationally expensive depending on the size of DAS data. Given that flow rates measured at different depths and different times are highly correlated, a more efficient algorithm can be developed that analyzes a large chunk of the DAS data at once to find the flow rates.

Wavelet Transform: We propose using an efficient image-processing algorithm based on the Wavelet transform (Mallat 2008). In the past decade there has been interesting applications of wavelets in the oil and gas industry, such as denoising data (Ouyang & Kikani 2002), pressure transient analysis (Dastan & Horne 2011), and identification of flow regimes (Wu et al. 2001). The wavelet transform is a convenient representation to study signal details and trends as a function of time/position.

Fig. 5 gives an outline of the algorithm we propose. In our method, 2D wavelet transform is computed within a given time interval. Different than the Fourier Transform approach above, only the most essential wavelet coefficients are computed, that are most relevant to flow rate estimation. Computing only the wavelet components relevant to the flow rather than the whole set improves computational efficiency substantially. We utilize the forward model developed in Part I to determine which wavelet components are relevant to flow rates and flow patterns in the wellbore.

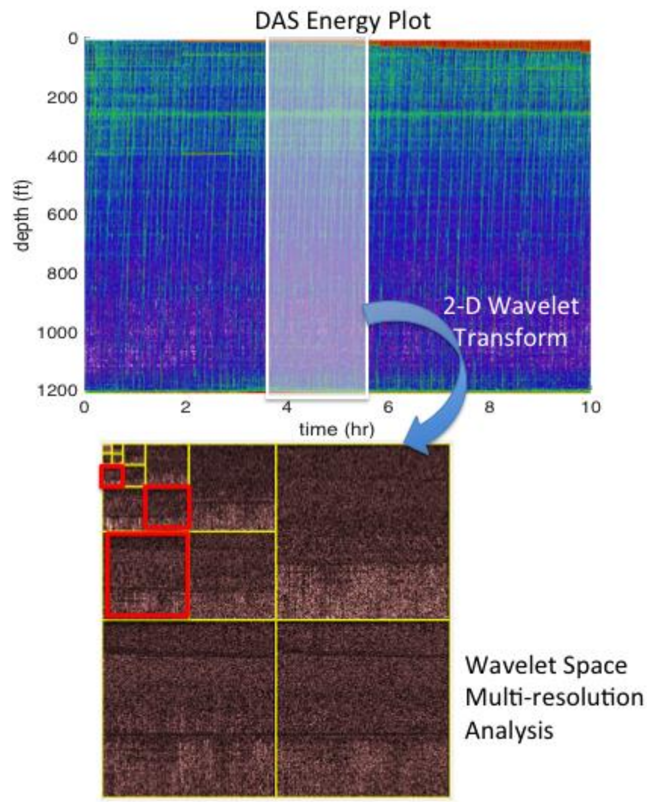

Fig. 5— Wavelet transform workflow: Using the forward model developed in this paper the wavelet components most relevant to the flow rate can be determined (red boxes). Subsequently, only a handful of wavelet coefficients need to be calculated from the DAS data to represent multiphase flow.

Machine Learning Approach: Once relevant wavelet coefficients are calculated, a deep learning algorithm utilizing artificial neural networks (ANN) is used for flow rate/flow pattern estimation. In the ANN model, the wavelet components are the input features and the flow rate and flow pattern are the outputs. To train the ANN model, the forward model we developed in this paper can be used to generate many sets of simulated DAS data for a variety of scenarios with known flow patterns and flow rates. Once trained, the ANN can be used with a DAS data set corresponding to an unknown flow pattern to find the most likely flow patterns and flow rates throughout the wellbore efficiently. The ANN model can be trained further using data from laboratory measurements, which will improve the accuracy of flow rate estimation.

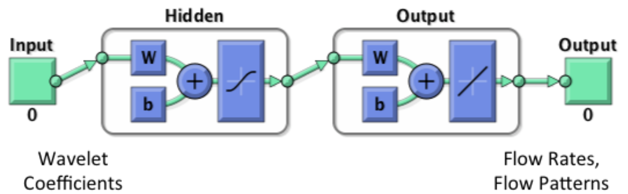

Fig. 6—The wavelet coefficients are used as input parameters in an artificial neural network model to estimate multiphase flow rates and flow patterns.

Application of our Technique

To test our technique, we generated synthetic well data with a depth of 6000 ft. The wellhead pressure is 2400 psi and the bottom hole pressure is 3900 psi, following production for 1000 days. Fluid temperatures at the wellhead and bottom hole are 135 °F and 182 °F, respectively. Wellhead flow rates were 2000 STB/d for oil with a formation volume factor of 1.33. The gas-oil ratio was assumed to be 2.2 Msfc/bbl.

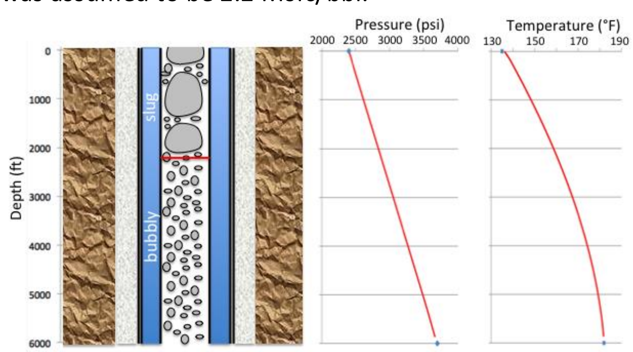

Fig. 7— Flow patterns and pressure and temperature profiles in the synthetic well example.

Fig. 7 shows the calculated pressure and temperature profiles in the well using the Hasan-Kabir technique. The flow pattern is bubbly from the bottom hole up to about 2000 ft depth, and then slug flow towards the wellhead.

Using the temperature and pressure profile, we calculated the speed of sound as a function of depth. Subsequently, we simulated DAS data corresponding to the steady-state flow condition in the well, as shown in Fig. 8.

Finally, we used the wavelet technique to analyse DAS data and find oil and gas flow rates as a function of depth, as shown in Fig. 9. As we go from the bottom hole towards the wellhead, the oil flow rate decreases and the gas flow rate increases.

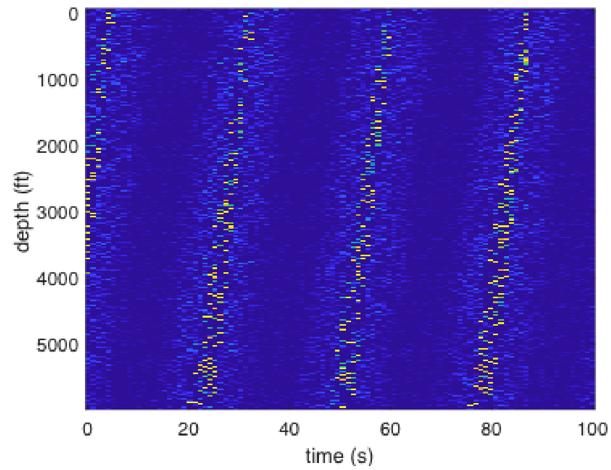

Fig. 8— Simulated DAS data for two-phase steady-state flow for our synthetic well example.

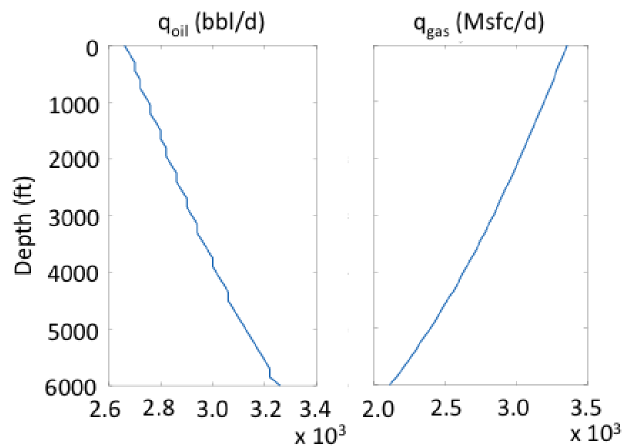

Fig. 9— Calculated oil and gas flow rate profiles in the well. Oil flow rate drops and gas flow rate increases towards the wellhead.

Conclusions

In this paper we discussed a method to measure distributed multiphase flow rate using distributed acoustic sensing. Summary and conclusions are as follows:

1. We developed a mathematical model taking into account several physical mechanisms that link the flow in the wellbore to DAS data. The forward model is crucial to develop a robust inverse model.
2. The forward model allows us to simulate DAS data corresponding to evolution of flow patterns in time, such as predominantly single-phase oil flow turning into oil-gas two-phase flow.
3. We developed a signal processing method based on the wavelet transform to process DAS data efficiently in real time. In this method we only process relevant components of DAS data for estimating multiphase flow rates in the wellbore.

4. The calculated wavelet coefficients are used as inputs to an artificial neural network that is trained to estimate flow rates and flow patterns. The neural network can be trained with both synthetic data (forward model) and experimental data.
5. Our algorithm significantly reduces the computational time and allows for real-time analysis of DAS data, which is crucial for timely operational decisions.

Recommendations

There are a number of areas this project will need to progress further. We envision the following:

1. Test and train the model with DAS data from flow loops and field DAS data with known bottom hole and wellhead flow rates.
2. Full field testing of the model and real time processing capability using existing DAS hardware in the field.
3. Design and implement new hardware that can do data processing internally and does not require transferring bulky data.

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Nomenclature

c_g	=	*speed of sound in gas, ft/sec*
c_m	=	*average speed of sound in liquid-gas mixture, ft/sec*
c_o	=	*speed of sound in oil, ft/sec*
c_r	=	*real gas specific heat ratio, dimensionless*
c_t	=	*speed of sound in tubing filled with fluid, ft/sec*
C_o	=	*flow parameter (ratio of the velocity at the center to the average velocity)*
d	=	*tubing inner diameter, ft*
E	=	*Young's Modulus of the wellbore, dyn/cm²*
f_g	=	*gas volume fraction, dimensionless*
f_L	=	*liquid holdup, dimensionless*
f_m	=	*Moody friction factor, dimensionless*
g	=	*gravitational acceleration, ft/sec2*
h	=	*tubing thickness, ft*
K_o	=	*bulk modulus of the oil phase, lbm/ft sec2*
M_r	=	*molecular weight of the gas, lb/mol*
p_p	=	*pressure perturbation in the fluid (as a result of acoustic wave), psi*
$p_{p,0}$	=	*amplitude of the pressure perturbation in the fluid, psi*
r	=	*radial coordinate, ft*
R	=	*universal gas constant, psia ft3/lb mol °R*
t	=	*time, sec*
T	=	*temperature, °R*
v_m	=	*superficial velocity of the gas-liquid mixture, ft/sec*
v_{sg}	=	*superficial velocity of the gas phase, ft/sec*
v_+	=	*velocity of the forward moving acoustic wave, ft/sec*
v_-	=	*velocity of the backward moving acoustic wave, ft/sec*
v_∞	=	*superficial velocity of the gas phase, ft/sec*
z	=	*coordinate along the axis of the wellbore*
Z	=	*gas compressibility factor, dimensionless*
α	=	*attenuation constant of the fiber, 1/ft*
ω	=	*angular frequency, rad/sec*
ρ_m	=	*density of the gas-liquid mixture, lbm/ft3*
ρ_g	=	*density of gas, lbm/ft3*
ρ_o	=	*density of oil, lbm/ft3*
φ	=	*angular coordinate, rad*

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