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Prediction of Gas Critical Flow Rate for Continuous Lifting of Liquids from Gas Wells Using Comparative Neural Fuzzy Inference System

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ABSTRACT

One of the most serious problems of gas wells is the accumulation of natural-gas condensates. During the operation of gas wells, it is probable that some liquids cannot be transferred outside by the use of gas flow and this results in fall of liquids to the down-hole and gradual loss of well. For solving this problem, the well must be drained by the use of gas lift or hydraulic pumps. Thus the subject of accumulation of liquids in gas wells is considered as one of the most important challenges of oil and gas industry. Surveying the gas drain mechanism shows a critical flow of gas for preventing from accumulation of liquids. Thus predicting the lowest rate of gas flow is very important for preventing from accumulation of liquids. Several models have been provided for calculating the critical velocity. The main aim of this research is predicting the lowest rate of gas flow for transferring liquids to the surface by the use of comparative neural-fuzzy intelligent systems in order to detect the formation or lack of formation of accumulation of liquids. The results of this prediction indicate the optimal performance of conducted modeling for predicting the lowest rate of gas flow.

KEYWORDS: Critical Velocity, Critical Flow of Gas, Accumulation of Liquids, Comparative Neural-Fuzzy Systems.

1. INTRODUCTION

Hydrocarbon gas is produced in underground reservoirs and in most cases it has liquid phase with it and it can affect the characteristics of flow of well. Liquids could be produced from natural-gas condensates and/or interstitial water in the reservoir matrix. During the gas production, some liquids may not be able to come out through the flow of gas and due to this they accumulate down-hole. By accumulation of liquids down-hole, the flowing pressure at the down-hole increases and it results in increased water saturation around the well and decreased effective gas permeability around the well. Thus the flow of produced gas decreases. Ultimately, liquid accumulation results in eliminating the gas well. Thus there is a critical velocity in the well for transferring liquids to the surface that in velocities lower than the critical velocity, gas is unable to transfer liquids to the surface and it results in formation of a liquid column in the well that decreases the productivity of the well and in velocities higher than the critical velocity, the liquids are transferred along with gas and the liquid accumulation down-hole is prevented [1-3].

As it was mentioned, the liquid accumulation phenomenon in gas wells results in decreased produced flow of gas; thus if the liquid accumulation is detected on-time, it is possible to reduce the damages caused by lack of gas production by the use of different methods of lifting the liquids from the well column. The most common and most applicable model of calculating the critical velocity is provided by Turner. Turner has provided two physical models for analyzing the permanent lifting of liquids from gas wells. These two models include liquid film movement along the walls of the pipes and the liquid droplets entrained in the high velocity gas core. Comparing these two models with field data it is concluded that theory of droplets model is a better theory for liquid accumulation and liquid film model has less effect on liquid accumulation [4].

Coleman et al (1991) proposed a model for predicting the liquid accumulation that its foundation was based on Turner's model without 20% increase of minimum gas flow [5]. In this model, in states which the ratio of liquid to gas is lower than 22.5 bbl/MMscf, it does not have an effect on determining the beginning of liquid accumulation and the gas flow is the dominant factor. Turner used data with wellhead pressure of 1000 psi but Coleman proved that Turner's formula with 20% increase for data with wellhead pressure less than 1000 psi is inefficient. Neviaser et al [6] provided a new equation for calculating critical velocity based on Turner's equation. They used Allen's model and considered the effect of fluid viscosity and flow regimes for calculating critical velocity. In their researches, Mian Lay et al. [7], found out that Turner's model and Coleman's model do not consider the change of shape of

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liquid droplets in free fall in the gas environment. They argue that liquid droplets are dragged in high velocities of gas flow and a pressure difference happens between the front and back of the droplets and droplets' shape changes by applying this pressure and their change of shape is from spherical to convex or flat. In 2002, El-Sayed et al provided a model for predicting the minimum flow pressure for continuous lifting of liquids from wellhead by the use of artificial neural networks. Comparing the performance of accuracy of new model and other models, they concluded that artificial neural networks model works better than all experimental models and the absolute error percentage of this model is 4.61% [8]. Olufemi et al (2005) provided a model for predicting the critical flow rate in low pressures for gas wells. Olufemi used laboratory data to calculate parameters to be the drag coefficient for cylindrical droplets; thus Olufemi considered that droplets' shape is cylindrical and provided a new model for predicting the liquid accumulation downhole [9]. Zhou et al (2010) introduced the droplet concentration model. The foundation of Turner's droplet pattern is the balance of forces for one droplet and it does not include the effect of clash of droplets. When the liquid droplets concentration is low the possibility of clash of droplets is lower and Turner's model works perfectly well. When the liquid waste is below or equal to threshold, the critical velocity of model is the Turner's model; when the liquid waste is more than the threshold the critical velocity changes and the critical velocity is calculated through the new model [10].

Wang Wei et al., (2010) provided a model for calculating the water-retention capacity in gas wells. This model is based on analysis of flow regimes during the production of gas wells with water and shape of particles as an elliptical disk instead of being spherical and changes are considered based on the existing forces [11].

There are different experimental methods based on Turner's model that predict the liquid accumulation in gas wells. Also, most experimental methods use droplets' model for calculating and predicting liquid accumulation. The current research aim is providing a model for eliminating the limitations of experimental models and more accurate prediction of critical flow in gas wells. Comparative neural-fuzzy systems are tools that could be used for predicting the liquid accumulation and reaching the desired goals. Next, the neural-fuzzy networks and parameters used in these networks are going to be introduced.

2. Comparative Neural-Fuzzy Networks

2.1. Soft Computing

Soft computing is a branch in computer science using the inexact solutions for solving problems that are complicated in terms of computing and they cannot be solved within an acceptable time [12]. Intelligent systems and especially hybrid systems are examples of using these traditional methods in this branch. Use of hybrid artificial intelligent systems is successfully developing. Some of their applications are process control, engineering design, simulation, prediction etc. The same as combination of fuzzy logic and neural networks, genetic algorithm and expert systems, the hybrid intelligent systems significantly increase the performance of network in problem solving. Each intelligent method has features that may be appropriate for a specific case and not all cases. Theoretically, neural networks and fuzzy inference systems (FIS) are equal but practically, each of them has advantages and disadvantages. For example, neural networks are appropriate tools for detecting the pattern and estimating the function but they are unable to justify their way for reaching the desirable result [13]. Thus, analyzing the trained networks is difficult and it is impossible to extract the decision making rules from them; however, fuzzy inference systems (FIS) are more desirable because their behavior could be defined based on rules and their performance could be interpreted by regulating rules. Fuzzy system explains the logic and the method of its decision making but it is unable to automatically regulate rules used for decision making. In neural-fuzzy systems, the neural networks could be used for regulating parameters related to membership functions in FISs and so the problem of time consuming manual regulation of parameters is solved [14].

2.2. Structure of a Neural-Fuzzy Network

Comparative neural-fuzzy inference system was firstly provided in 1993 by Jang. This system acts as a fuzzy decision making tree for classifying data to one of the 2^n or p^n linear regression models in a way it results in minimizing the sum of squares for errors [15].

If there is knowledge based on fuzzy language rules, then it is possible to create FIS and having the data it is possible to use neural networks. For creating a FIS it is required to detect fuzzy sets, fuzzy operators and foundation of the existing knowledge and for creating a neural system the user must determine the structure and learning algorithm [16]. Researchers have shown that each of these methods have problems on their own; thus it is normal to combine these two methods to improve the level of these methods. The FIS could not learn thus the learning ability is important for FIS; and the structure of language rules is important for the neural networks. In the structure of a neural-fuzzy system, ANN learning algorithms determine the parameters of a fuzzy inference system. In a neural-fuzzy system, the structures participate based on the data and based on the perception, as the input data. The usual method of using this learning algorithm in FIS is that the FIS is provided in a structure such as neural networks [17, 18].

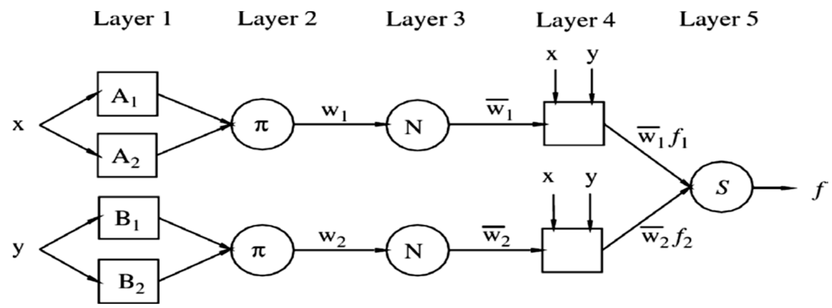

Fig. 1. Structure of Comparative Neural Fuzzy Inference System (ANFIS) [17]

As Fig. 1 shows, generally, an ANFIS has 5 layers. Layer 1, input nodes: each node of this layer is a membership grade attributed to each of the input variables of the model (X and Y). Membership grades are determined based on the attachment of inputs to each fuzzy set of A_i and B_i; in other words, the output of each node in this layer is the membership grade attributed to the input variables in fuzzy sets which is stated as follows:

$O_i^1=\mu_{Ai}(x), \quad i=1, 2\ldots, n$
$O_i^1=\mu_{Bi}(y), \quad i=1, 2\ldots, n$

In the above equation, x and y are non-fuzzy inputs for i^{th} node and A_i and B_i are fuzzy membership functions. Also membership grade of each input is determined as the output of first layer as μ_{Ai} (x) and μ_{Bi} (y). Thus the parameters of membership functions which are known as the parameters of the prior part of fuzzy rules, and are classified as non-linear parameters must be determined.

Layer 2: Includes the node rules; in this layer, each node calculates the firing strength of a rule. In this layer, operator AND is used for calculating the firing strength of each rule. O^2_i indicates the output of K^{th} node in the second layer and it is the product of all incoming signals:

$O_i^2=W_i = \mu_{Ai}(x)\,\mu_{Bi}(y)\ , i=1,2,\ldots,n$

Layer 3: Includes normalized nodes and calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths; as a result this layer is provided in the following equation:

$O_i^3=\overline{w}_i=\frac{w_i}{\sum_{i=1}^{n} w_i} \quad i=1,2,..\ ,n$

Layer 4: Layer 4 is the de-fuzzy layer. In this layer, each node by multiplying its normalized weight in the lower part of if-so fuzzy rules, affects the estimation of system output:

$O_i^4=\overline{w}_i f_i=\overline{w}_i(p_i x + q_i y + r_i) \quad i=1,2,..\ ,n$

Layer 5: In this layer all incoming signlas are summed and this summation of all incoming signlas is the overall system output:

$O_i^5=\sum_{i=1}^{n}\overline{w}_i f_i \quad i=1,2,...$

3. Selection of Training Data and Test

For predicting critical flow for developing a neural-fuzzy model the first step is determining appropriate inputs and outputs for the system. The data required for designing and training the designed model is extracted from researches related to surveying the prediction of liquid accumulation for removing liquids from gas wells [9]. In this study the inputs of neural-fuzzy model of wellhead are temperature, produced gas density, rate of produced liquids, ratio of liquid to gas, apparent velocity of gas, and apparent velocity of liquid. The cross-section production of well is not considered as input data because it is fixed and the output of network is the critical flow of well. The total number of used data is 84 divided to two parts, network training data (42) and test data (42).

4. RESULTS AND DISCUSSION

In neural-fuzzy method the comparative neural-fuzzy inference system was used. Gaussian membership functions were extracted by subtractive clustering for each input and its optimal parameters were calculated by the use of neural system and hybrid algorithm. In neural-fuzzy method, the most appropriate range of influence for predicting the critical flow is 1.15. In table (1) the best created model compared to real results and the latest model provided are shown, in which TAAE% is the total mean of absolute error percentage and R_n is the correlation coefficient for normalized data and they are respectively calculated through the following formula:

$$\mathrm{TAAE\%} = \left(\frac{100}{n}\right)\sum_{i=1}^{n}\frac{\lfloor p_{e,i} - p_{m,i}\rfloor}{p_{e,i}}$$

$$R_n = \frac{\sum_{i=1}^{n}[(p_{m,i} - p_{m,av}) * (p_{e,i} - p_{e,av})]}{\sqrt{\sum_{i=1}^{n}[(p_{m,i} - p_{m,av})^2] * \sum_{i=1}^{n}(p_{e,i} - p_{e,av})^2}}$$

In the above mentioned formula, $p_{e,i}$, $p_{m,i}$, $p_{e,av}$, and $p_{m,av}$ are respectively the desired (laboratory) output,the output predicted by the network, mean of laboratory values, mean of predicted values and n is the number of data used for training or testing the network.

Based on table 1, the provided ANFIS model has more accuracy than El-Sayed's (neural networks) model, in a way that total mean of absolute error percentage for the neural-fuzzy model is much lower than the neural networks model.

Table 1. Comparing the performance of different models for predicting the minimum critical gas flow.

	AAE%	R
ANFIS mode	0.0466	1
Neural Network(El-Sayed)	4.61	0.9911

For evaluating the comparative neural-fuzzy model, the achieved output of model is compared with actual values. This comparison is shown in figure 2. As the figure has shown, the correlation coefficient between the modelachieved from comoarative neural-fuzzy system and actual values is 1 which is very good. The results of ANFIS model match very well with the actual results and show the high efficiency of this model.

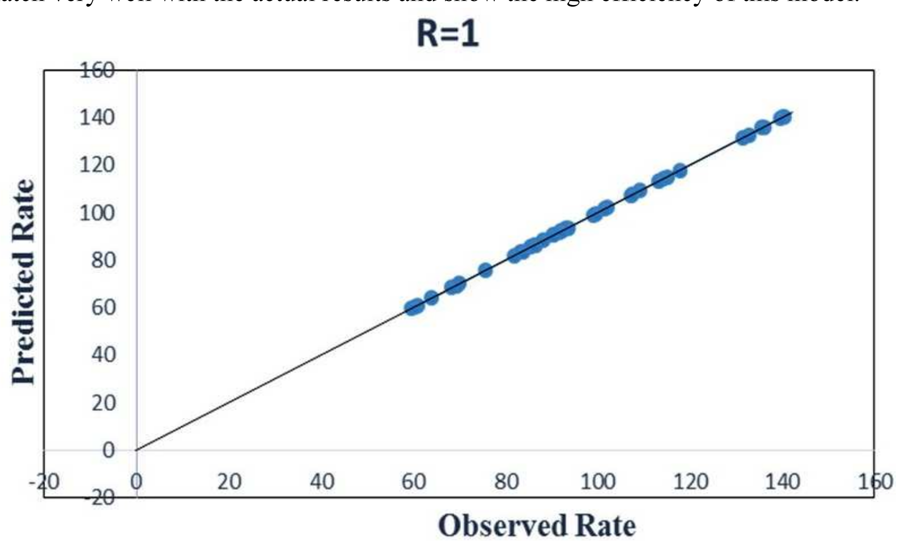

Fig. 2. Correlation between neural-fuzzy inference system model and actual values.

Ultimately, for choosing the best model for predicting the gas flow rate, the comparison of results of comparativeneural-fuzzy model with mathematical models is provided in table 2. As it is observable, data predicted by the network has the highest conformity with the laboratory data; whereas the mathematical models have several errors; thus the accuracy of this method is more than the previous method and it provides a better prediction and this shows the accuracy and efficiency of this model.

Also there is no need to calculations related to formula achieved by mathematical modeling. There is no need for recalculation for making a change in data such as increasing or decreasing them and/or changing the parameters of the network; and this shows the flexibility of the network.

Figure 3 shows the comparison of critical flow of different mathematical models and ANFIS model with critical laboratory flow based on pressure. As the figure shows, critical flow of ANFIS has high conformity with laboratory data; whereas the mathematical models are linear and this indicates the flexibility of neural-fuzzy network compared to mathematical models. Another note that must be taken to account is that Turner's method is applicable for pressures above 1000 Psi and Coleman's meethod is applicable for pressures under 1000 Psi; thus different mathematical models are required for different pressures; whereas, there is no pressure limitation for comparative neural-fuzzy networks and they are capable of predicting critical flow for all pressures.

Table 2. Comparison of critical flow of neural-fuzzy model with mathematical models.

Tubing Pressure (Psia)	Lab. Critical Rate (Mscf/d)	Turner's Critical Rate (Mscf/d)	Coleman's Critical Rate(Mscf/d)	Li's Critical Rate (Mscf/d)	Olufemi's Critical Rate (Mscf/d)	Anfis model Critical Rate(Mscf/d)
14.82	59.69	100.23	83.52	39.22	64.61	59.6924
15.01	64	100.87	84.06	39.48	65.02	64.0006
15.02	69.96	100.9	84.08	39.49	65.04	69.9698
15.11	93.13	101.21	84.34	39.61	65.24	93.1087
15.18	102.17	101.44	84.53	39.7	65.39	102.1602
15.22	90.36	101.57	84.64	39.75	65.47	90.3402
15.42	107.29	102.24	85.19	41.01	65.9	107.2586
17.02	86.41	107.4	95.5	42.03	69.23	86.371
20.21	99.13	117.03	97.52	45.8	75.43	99.1439
21.11	69.36	119.6	99.66	46.81	77.09	69.4398
22.31	83.38	122.95	102.45	48.12	79.25	83.379
23.07	81.94	125.02	104.18	48.93	80.59	81.909
24.07	61.02	127.7	106.41	49.97	82.31	61.04
25.37	68.33	131.1	109.24	51.3	84.5	68.3
25.66	88.16	131.84	109.86	51.59	84.98	88.18
25.66	101.5	131.85	109.87	51.6	84.99	101.478
26.13	115.01	133.06	110.88	52.07	85.77	115.022
26.18	140.12	133.17	110.97	52.12	85.84	140.128
16.37	136	133.65	111.37	52.3	86.15	136.003
26.66	85.41	134.4	111.99	52.59	86.63	85.416
27.03	109.18	135.33	112.77	52.96	87.23	109.176
27.33	131.39	136.07	113.39	53.25	87.71	131.39
29.61	140.03	141.62	118.01	55.42	91.29	140.307
30.18	83.71	142.98	119.14	55.95	92.16	83.694
30.81	91.69	144.46	120.38	56.53	93.12	91.694
31.65	90.32	146.4	122	57.29	94.38	90.339
31.65	114.41	148.7	123.91	58.19	95.85	114.4
33.13	117.84	149.8	124.83	58.62	96.56	117.844
34.69	99.55	153.28	127.72	59.98	98.8	99.572
35	139.47	153.97	128.3	60.25	99.24	139.443
38.66	60.46	161.8	134.83	63.32	104.29	60.449
39.31	93.61	163.14	135.94	63.84	105.16	93.602
40.31	92.08	165.2	137.66	64.65	106.48	92.057
40.68	107.49	169.95	138.29	64.95	106.97	107.508
43.19	92.2	171	142.49	66.92	110.22	92.200
45.13	86.17	174.77	145.64	68.4	112.66	86.177
45.13	75.5	174.77	145.64	68.4	112.66	75.524
45.13	86.22	174.77	145.46	68.4	112.66	86.2203
47.19	113.27	178.72	148.93	69.94	115.2	113.29
48.31	135.63	180.82	150.68	70.76	116.55	135.62
48.31	132.72	180.82	150.68	70.76	116.55	132.832
Cumulative Error Percent		42.69	18.90	44.15	8.019	0.00113
Absolute Error Percent		49.68	30.84	41.88	19.63	0.0466

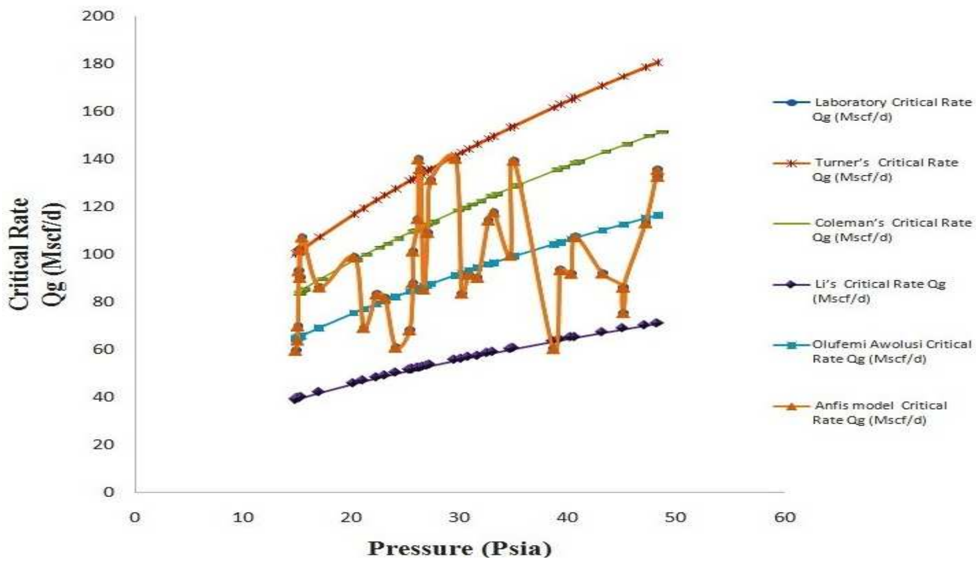

Fig. 3. Comparison of critical flow rate of neural-fuzzy model and different models based on pressure.

5. Conclusion

- ❖ For critical flow rate modeling, ANFIS (Genfis2) model could be used as a reliable model within the area of training situation for predicting the critical flow.
- ❖ In this study, the critical flow rate and liquid accumulation in gas wells was estimated by the use of neural-fuzzy method. The applied method is cost-effective, quick and accurate. The correlation coefficient of critical flow rate is 1; and the mean absolute error is 0.0466. Therefore, it is suggested to use this method for estimating the critical flow rate.
- ❖ The current research shows the efficiency and flexibility of neural-fuzzy model in predicting the liquid accumulation and critical flow rate in gas wells. The superiority of this model to other experimental models of predicting liquid accumulation is clear.
- ❖ It must be noted that the more the number of training data the better the efficiecny of the network.
- ❖ If the number of data changes, there is no need to recalculate and this shows the flexibility of the network.
- ❖ The provided model has eliminated the necessity of complicated calculations and mathematical models and it is used with high accuracy for predicting the liquid accumulation.

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