VIRTUAL MULTIPHASE FLOW METER WITH TIME SERIES - TIME DELAY ARTIFICIAL NEURAL NETWORK UTILIZING MEASUREMENT DATA FROM WELL ORIFICE FLOW METER

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ABSTRACT

MPFM (Multiphase Flow Meter) is an equipment that measures multiphase flow in real time without the need for phase separation and widely used for testing oil and gas wells. The development of a virtual multiphase flow meter is intended to replace a multiphase flow meter which quantifies the flow rate of gas, oil, and water in real time without phase separation. VMPFM can be used as a backup measurement during well testing of oil and gas when MPFM is unavailable, thus increasing redundancy. The paper proposes modeling of VMPFM uses the time series-time delay of an artificial neural network from measurement data obtained from existing well orifice flow meter as parameter data input. Actual measurement data of the well on the offshore platform for a two-year duration are used for VMPFM modeling. The data set is divided into two sections: the first for training the model and the second for validation. Simulation results show that the method of time series-time delay using a thirty-parameter input delay time gives the most accurate measurement and fast simulation with a training duration less than 7 minutes. The best average discrepancy of gas rate, oil rate, and water rate are 6%, -16.4%, and -2.4%, respectively, between VMPFM and actual measurement by MPFM during the validation stage.

Key Words: Virtual multiphase flow meter, Multiphase flow meter, artificial Neural Network, time series-time delay, well orifice flow meter

1 Introduction

Multiphase Flow Meter (MPFM) is an instrument that can measure multiphase flow in real time without the need for phase separation and is commonly used to test oil and gas wells on offshore platforms, for example in the Mahakam Block (Fig. 1) in the province of East Kalimantan, Indonesia (Fig. 2). Individual well testing is required in the oil and gas industry since the multiphase flow rate figure is important for reservoir estimation, reservoir management, and production allocation [1]. Based on operation experience, the use of MPFM has several weaknesses, including electronic components that are prone to damage and expensive procurement costs as well as maintenance costs. This prompted the research development on VMPFM (Virtual Multiphase Flow Meter), a software-based computational model that can estimate multiphase flow rates by utilizing parameters from sensors located in the well. There are several advantages to using VMPFM, including providing backup measurement to existing MPFM, increasing the reliability and redundancy of well testing, and reducing capital and operational expenditure [2]. Another advantage of using VMPFM is the ease of implementation at a low cost because it utilizes existing sensors in each well. In addition, VMPFM can be implemented by combining field sensors with a distributed control system (DCS) using a supervisory control and data acquisition (SCADA) system or Internet of Things (IOT) infrastructure, so that personnel can access well-tested data figures in real time.

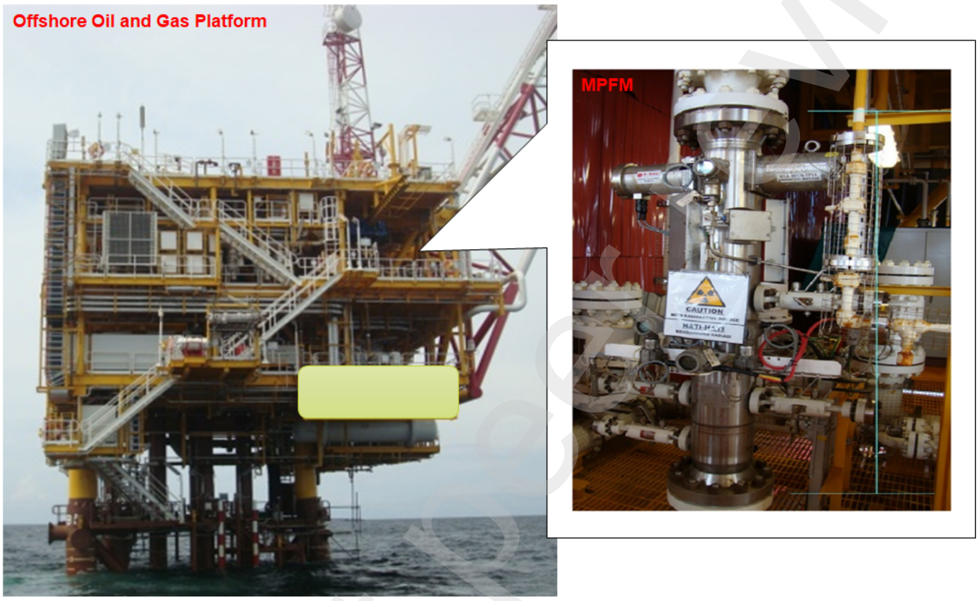

Fig. 1. MPFM in the Offshore Oil and Gas Platform

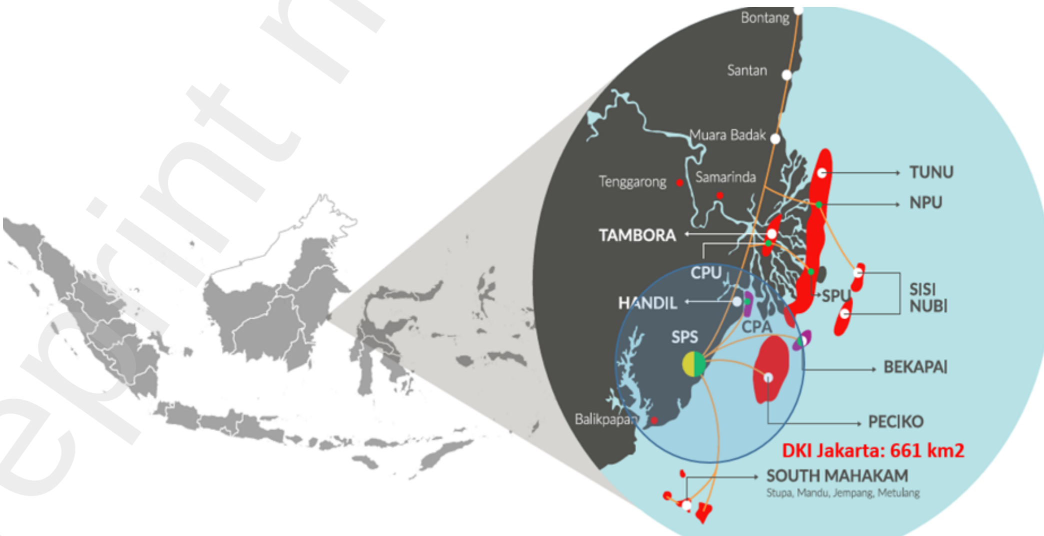

Fig. 2. Mahakam Oil and Gas Block in East Kalimantan Indonesia

Researchers have been working on the creation of VMPFM for several decades [3,4] using data-driven methodologies based on machine learning techniques. Prior to the development of multiphase flow prediction, research in the oil and gas industry made substantial use of artificial neural networks (ANN), a machine learning technique. ANN approaches were used by Al Abduljabbar et al. [5] to forecast the rate of penetration for the S-shaped well profile using surface drilling data. The optimal architecture of an ANN consisted of a single layer, 29 neurons, a tan-sigmoid transfer function, and a Levenberg Marquardt training function. The model showed an average correlation coefficient of around 0.93 and a root mean square error (RMSE) of 6.2%. Elgibaly et al [6] used two methods of ANN which are Radial Base Function (RBF) and Back Propagation Function (BPF) to predict three factors of gas lift optimization: optimal gas injection rate, bottom hole pressure, and flow rate. The experimental results indicated that the RBFNN-based model is a more reliable predictor, with an MSE value of 0.003.

Using parameters from drilling operations, such as Plastic Viscosity (PV), Mud Weight (MW), flow rate (Q), Yield Point (YP), Revolutions per Minute (RPM), Weight on Bit (WOB), nozzles total flow area (TFA), and Uniaxial Compressive Strength (UCS), Alkinani et al. [7] used a recurrent neural network model to estimate The Rate of Penetration (ROP). The simulation demonstrated that an R2 value of 0.94 is produced by the ROP prediction. In order to identify flow patterns, Al Naser et al. [8] combined an Artificial Neural Network (ANN) pre-processing stage with natural logarithmic normalization with feed-forward back propagation techniques. The model employed the Liquid Reynolds Number, Gas Reynolds Number, and Pressure Drop Multiplier as its three dimensionless parameters. For a variety of flow circumstances, it classified the flow patterns with greater than 97% accuracy. Arjun et al [9] proposed an ANN model based on a feed-forward back propagation technique that can accurately estimate and interpolate average reservoir pressure, predict the performance of oil production within water injection reservoirs, and address the problem of pipeline damage. The presented models' prediction performance yielded output values with average absolute relative errors ranging from 0.04 percent to 9.29 percent.

An initial study of neural network architecture for multiphase flow prediction has been developed by Sheppard et al. [10] to infer flow regimes and predict individual multiphase flow rates. Elmabrouk et al. [11] have utilized a Feed Forward Back Propagation artificial neural network (FFBP-ANN) to predict oil reservoir production performance using real data from Libyan oil fields. The best results have been obtained by using two hidden layers: thirteen nodes in the first layer and eight nodes in the second layer. The network provides reservoir oil rates with an average absolute error of 358 BOPD and an average absolute relative error of 11.97%. Other research has also been conducted by Hasanvand [12] using the FFBP-ANN method. The parameters used in this study as a reference are pressure and temperature at the wellhead. The number of hidden layers used is seven, and the learning algorithm used is Levenberg-Marquardt (LM). The sigmoid transfer function is used in the hidden layer, and the linear transfer function is used in the output layer. As the two previous studies, prediction of oil production using FFBP-ANN has also been carried out by Muradkhanli [13]. The hidden layer is used as much as one layer with three neurons. A variation of 70% of the total data is used for training.

Another research study by Bahrami et al. [14] for the prediction of multiphase flowrate has been carried out using the FFBP-ANN method and pressure signal analysis. The ANN transfer function uses is LM using two hidden layers. The verification results show that there is a correlation between the predicted results and the actual value, and the determination coefficient (R^2) is larger than 0.995. Azim [15] has also used FFBP-ANN to predict oil production. The learning algorithm is the scale conjugate gradient (SCG). In this study, accuracy performance testing is carried out by varying the number of layers and the number of neurons. The simulation results show that the optimal number of hidden layers is one layer and two neurons.

A different method has been used by Al-Qutami et al. [16] in the development of VMPFM. Ensemble neural network techniques and regression trees that utilize bootstrapping are used to generate diversification among learners. The VMPFM model is then validated using real data for five years from eight wells. Several parameters are used as input data, including pressure and temperature at the wellhead, pressure and temperature at the reservoir, upstream and downstream choke valve pressure, and choke valve opening. The simulation results show that the resulting average errors are 1.5%, 6.5%, and 4.7% for predictions of gas, oil, and water flow rates, respectively. Other VMPFM research has been conducted by Al-Qutami et al. [17] using diverse neural networks and adaptive simulated annealing optimization to select the best learner. The method is evaluated against well test data and obtained an average error of 4.7% and 2.4% for liquid and gas flow rates, respectively.

Andrianov et al. [18] have used the long short-term memory (LSTM) method to predict multiphase flowrate. The forecasts show that the gas flow rate is overestimated when compared to the actual gas rate, whereas the predicted liquid flow rate is very close to the actual liquid rate. Ahmadi et al. (2013) [19] have implemented fuzzy logic, ANN, and the imperialist competitive algorithm (ICA) to predict oil flow rate. The line's temperature and pressure are used as inputs from 50 wells. The results prove the effectiveness, robustness, and compatibility of the ICA-ANN model. Gorbani et al. [20] use five machine-learning algorithms with a dataset of 1037 records (830 used for training and 207 for testing) to predict the flow rate with reliable accuracy. The algorithms evaluated are adaptive neuro fuzzy inference system (ANFIS), least squares support vector machine (LSSVM), radial basis function (RBF), multilayer perceptron (MLP), and gene expression programming (GEP). The results show that the MLP algorithm achieves the most accurate predictions of orifice meter flow rates. GEP and RBF also achieve high levels of accuracy. ANFIS and LSSVM perform less well, particularly in the lower flow rate range.

Farsi et al. [21] have applied the multi-layer perceptron (MLP) algorithms coupled with artificial-bee colony (ABC) and firefly (FF) swarm-type optimizers for oil flow rate prediction through the orifice plates. The model has achieved the highest prediction accuracy of RMSE at 8.70 stock-tank barrels of oil per day. Grimstad et al. [22] have introduced a probabilistic VFM based on Bayesian neural networks. The method consists of 60 wells across five different oil and gas assets resulting in averages error of 4%–6% and 8%–13% for the 50% best performing models. Choubineh et al. [23] have hybridized an artificial neural network (ANN) with a teaching-learning-based optimization (TLBO) algorithms, involving 6 input variables to predict liquid critical-flow rate through wellhead chokes of producing oil wells. The model uses a data set of 113 wellhead flow tests from oil wells in South Iran with performance accuracy of coefficient of determination by 0.981; root mean square error by 714; average relative error by 2.09%; and average absolute relative error by 6.5%.

Based on previous research for developing VMPFM and predicting multiphase flowrate, the measurement data of the well orifice meter has not yet been considered as a parameter data input for creating the ANN model. In addition, there is still no work exploring time series-time delay neural network techniques in developing the model. Several studies have also showed that the duration for training the model is considered long enough, which can take several hours to get the model to reach convergence with hundreds of iterations. The paper, therefore, proposes a novel method by developing a VMPFM model using the time series-time delay artificial neural network method (TSTD-ANN) and utilizing measurement data from an existing well orifice flow meter as parameter inputs. Another objective is to keep the duration of the training simulation for each well as short as possible in order to achieve convergence, because duration is important in the industry considering the need to perform dozens of well tests per day.

2 Materials and Methods

The development of VMPFM requires several parameters from producing oil and gas wells as input data to ANN simulations. As for the several research references, no study has included the measurement data of the well orifice flow meter as a parameter data input in the development of the VMPFM model. Based on the initial hypothesis, the more parameter data input that is included, the more reliable and accurate the VMPFM model is expected to be. Therefore, in this study, the well orifice measurement data of pressure, temperature, and flow rate are added to the ANN simulation as well as other measurement data such as pressure and temperature from the wellhead, choke valve opening, and multiphase flow rate data for each gas, water, and oil phase during well testing by MPFM. Real data from an oil and gas well on one of the offshore platforms in the Mahakam Block, East Kalimantan Province, Indonesia, is used in this study.

Routine well testing is carried out on average four times a month, where each test is conducted for a minimum duration of four hours with data sampling every five minutes. The real test data is stored in the distributed control system (DCS) server and then extracted during the last two years, from May 2020 to October 2021, for the requirement of the VMPFM ANN simulation. There are six parameter input data, such as wellhead pressure and wellhead temperature (P1 and T1), choke valve opening (%CV), and pressure, temperature, and flow rate from the well orifice flow meter (P2, T2, Qgas). Three parameters target data for ANN simulation are used, including gas, oil, and water flow rates (Qgas, Qoil and Qwtr) from the measurement by MPFM. Schematic nine data parameters used in the development of the VMPFM model can be seen in Fig. 4.

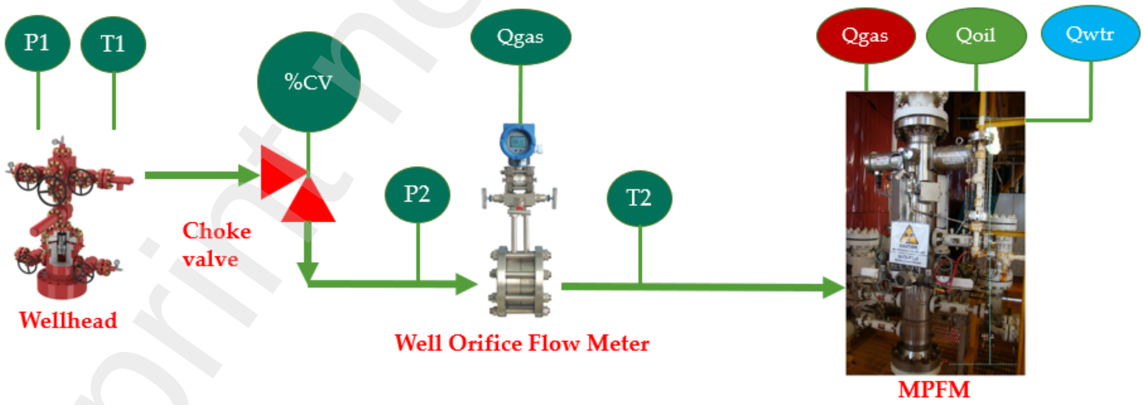

Fig. 4. Schematic nine data parameters used in the development of the VMPFM

There are several steps in the methodology for the VMPFM development, which consist of preprocessing data, building ANN models, training (learning, validating, and testing) the model, verifying the accuracy of ANN models, predicting data using ANN models, and validating ANN models. The schematic of the VMPFM development methodology can be seen in Fig. 5. The first step of VMPFM development is initial data processing before the six input variables and three output variables are used in the ANN simulation. This is necessary to remove damaged or bad data. In addition, the input data normalization process is also carried out to make ANN simulations fast and efficient. The goal of normalization is to convert the input data into a range between -1 and 1 so that simulations can be performed quickly on many artificial neural networks. Normalization can be explained by the following equation 1 [23]:

$$y = \frac{(y_{max} - y_{min}) * (x - x_{min})}{(x_{max} - x_{min})} + y_{min} \tag{1}$$

Where y is normalization output value matrix, x is input value matrix, y_{min} is scalar number with default value -1, y_{max} is scalar number with default value 1, x_{min} is Matrix minimum input value, x_{max} is Matrix maximum input value.

3 Time Series - Time Delay Neural Network

After data processing has been completed, the second step is the development of the VMPFM model using a time series-time delay artificial neural network (TSTD-ANN) [24]. In this method, variations in the time delay of the input data are carried out to observe the effect of transients from time variations on the performance accuracy of the VMPFM model. The paper considers the modeling of VMPFM uses TSTD-ANN to estimate the multiphase flow rate of oil, water, and gas in producing oil and gas wells.

The ANN terminology is inspired by the biological network of neurons in the brain, where the network is formed by billions of neurons that are connected to each other to be able to carry out several biological functions such as moving, thinking, and speaking [25]. The dynamic of TSTD-ANN, also referred to as backpropagation through-time [26], is one of the ANN algorithms that considers the presence of transient factors in the form of delays in the input data time. TSTD-ANN is often used for forecasting time series data. This is because the data at the present time (t) is related to the data at the previous time (t-1), so the time factor becomes important to be included in the ANN simulation. An explanation of how TSTD-ANN works can be seen from the schematic in Fig 3.

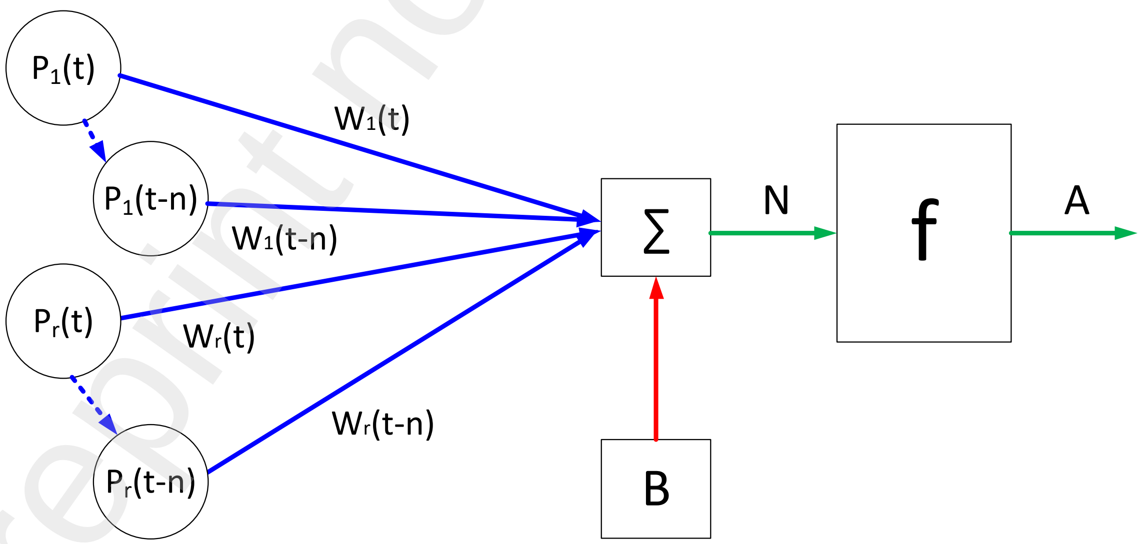

Fig. 3. Schematic of time series - time delay ANN

The simple block diagram formula can be explained using the following equation 2 [24]:

$$A = f([P_1(t)w_1(t)] + [P_1(t-n)w_1(t-n)] + [P_r(t)w_r(t)] + [P_r(t-n)w_r(t-n)] + B) \quad (2)$$

where $P_1(t)$ is Input value number 1 on time t, $P_r(t)$ is input number r on time t, $w_1(t)$ is weight number 1 on time t, $w_r(t)$ is weight number r on time t, $P_1(t-n)$ is Input value number 1 on time t-n, $P_r(t-n)$ is input number r on time t-n, $w_1(t-n)$ is weight number 1 on time t-n, $w_r(t-n)$ is weight number r on time t-n , n is number of delay time, r is number of parameter input, t is current time, f is transfer function, B is bias number, and A is output value.

There are several transfer functions in ANN. As for this VMPFM study, only two types of transfer functions are used, namely the linear function and the sigmoid function [23]. The learning algorithm uses supervised learning. This is because the neurons in the ANN are equipped with data sets in the form of input data and output data, which are the learning targets. This data set can be used to train the VMPFM model that has been created. The purpose of supervision learning is to train the model by changing the weight values so that the error between the output results and the input values can be minimized.

On the developed model, several neurons with six parameter input data, two hidden layers, and three parameter output data are used. A schematic of the TSTD-ANN method along with the input data and the output data can be seen in Fig. 6. The third step is the training phase, which consists of learning, validating, and testing the VMPFM model that has been created using the TSTD-ANN method. The learning algorithm in ANN consists of several methods. As for this research, two methods are used, namely Levenberg-Marquardt (LM) [27] and Scaled Conjugate Gradient (SCG) [23]. As an illustration of how the learning algorithm works in ANN, the simplest optimization algorithm, namely gradient descent is carried out using equation 3 below until convergent conditions are reached or in other words the error magnitude is as expected [23].

$$x_{k+1} = x_k - \alpha_k g_k \quad (3)$$

Where x_{k+1} is vector of weight and bias at t+1, x_k is vector of weight and bias at t, α_k is learning rate, g_k is Gradien at t.

The LM algorithm combines the Gauss-Newton algorithm and gradient descent. This algorithm has several advantages, which are: 1). Algorithm with the fastest learning among other algorithms, 2). This algorithm works well in non-linear regression, especially in curve-fitting problems [23]. However, the LM algorithm is less efficient for complex networks with thousands of data weights because it requires a large memory capacity and longer computation time. In general, the LM algorithm can be explained using equation 4 below. The α_i value is set to a large value at the start of the iteration and decreases slowly to zero as the iteration process runs so that its characteristics change from the previous steepest descent algorithm to Newton's algorithm [23].

$$x_{i+1} = x_i - [[J_i] + \alpha_i[I]]^{-1}\nabla f_i \quad (4)$$

Where x_{i+1} is vector of weight and bias at t+1, x_i is vector of weight and bias at t, α_i is learning rate, J_i is Hessian Matrix, I is Identity Matrix, ∇f_i is gradient of the function.

The Scaled Conjugate Gradient (SCG) algorithm is recommended in complex ANNs because it requires relatively small memory and is much faster than the standard gradient descent algorithm. The formula of the SCG algorithm can be explained using the equation 5 below [23]:

$$x_{i+1} = x_i + \lambda_i\left[-\nabla f_i + \left[\frac{|\nabla f_i|^2}{|\nabla f_{i-1}|^2} \times (-\nabla f_{i-1})\right]\right] \quad (5)$$

Where x_{i+1} is vector of weight and bias at t+1, x_i is vector of weight and bias at t, ∇f_i is gradient of the function at t, λ_i is optimal step length, ∇f_{i-1} is gradient of the function at t-1.

In the fourth step, verification of the VMPFM model that has been trained is carried out. Several methods are used to verify the performance accuracy of the model which are Mean Square Error (MSE) [25], coefficient of correlation (R) [25] and Mean Absolute Percentage Error (MAPE) [28]. The tolerance limit is defined based on trial and error with the value of MSE is less than or equal to 1500, the R value is greater than or equal to 0.95, and MAPE value is less than or equal to 0.65.

R is the ratio between the covariances of two variables which aims to measure the linearity relationship between two data sets. The correlation coefficient value is between -1 and 1. Two variables are said to be correlated if the value of R is close to 1 or -1, whereas if the value of R is close to 0 then the two variables are said to be uncorrelated. Calculation of the correlation coefficient can be explained using the following equation 6 [25]:

$$R(x,y) = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma_x}\right)\left(\frac{y_i - \bar{y}}{\sigma_y}\right) \quad (6)$$

Where σ_x is standard deviation of variable y, x_i is variable x, $\bar{x}$ is Mean of variable x, y_i is variabel y, $\bar{y}$ is mean of variable y, n is sample number, R is coefficient correlation value.

MSE is the average of the squared error between the estimated and actual values which is normally used to calculate the global error. The MSE value is always positive and decreases as the error value approaches zero. MSE can be calculated using following equation 7 [25]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \quad (7)$$

Where t_i is target value at i, a_i is output value at i, n is sample number, MSE is mean square error. MAPE is the absolute error in percentage between the predicted value and the actual value. It can be calculated using equation 8 below [28]:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{t_i - a_i}{t_i}\right| \quad (8)$$

Where t_i is target value at i, a_i is output value at i, n is sample number, MAPE is mean absolute percentage error.

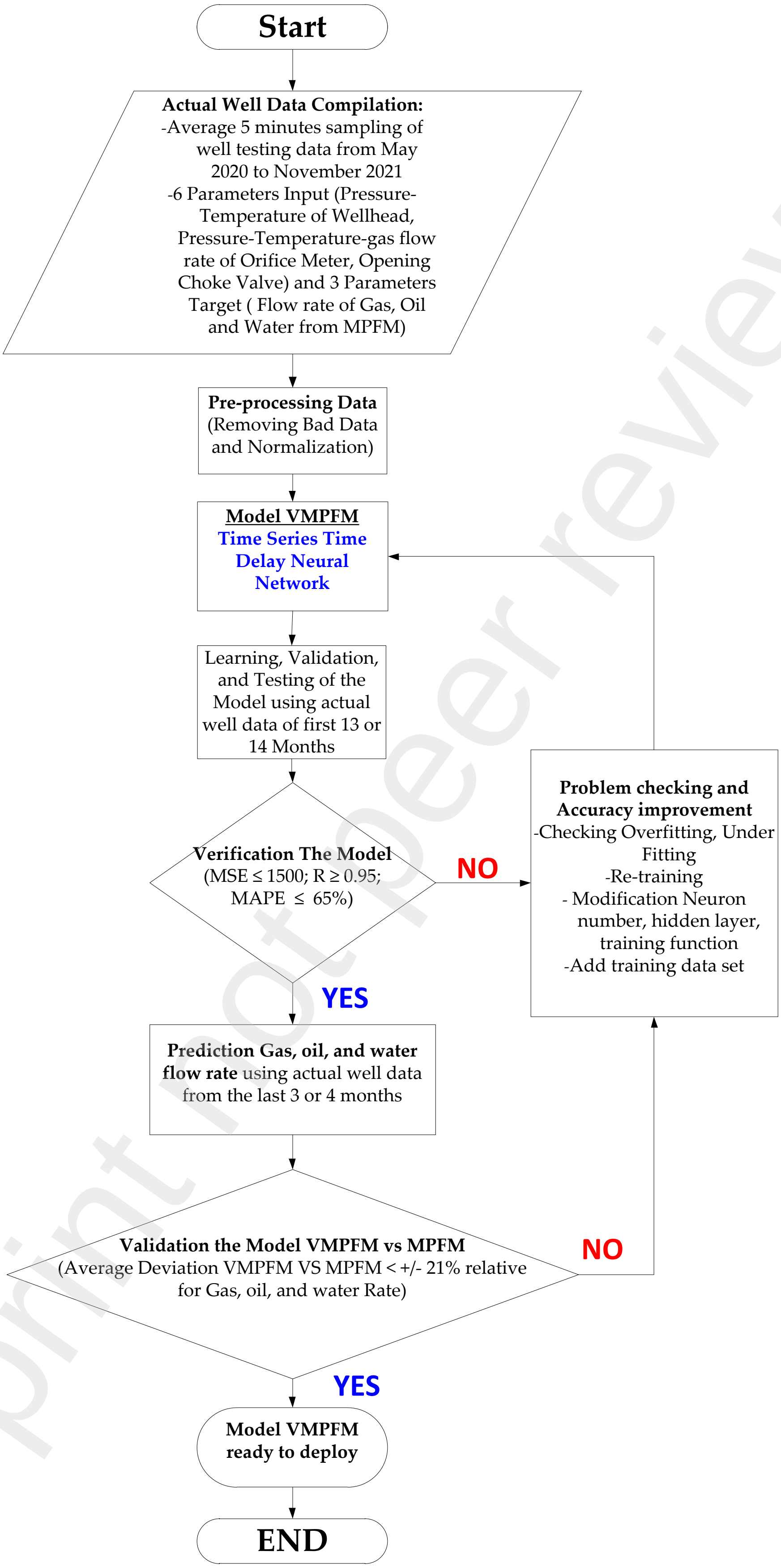

Fig. 5. Flow chart of VMPFM development

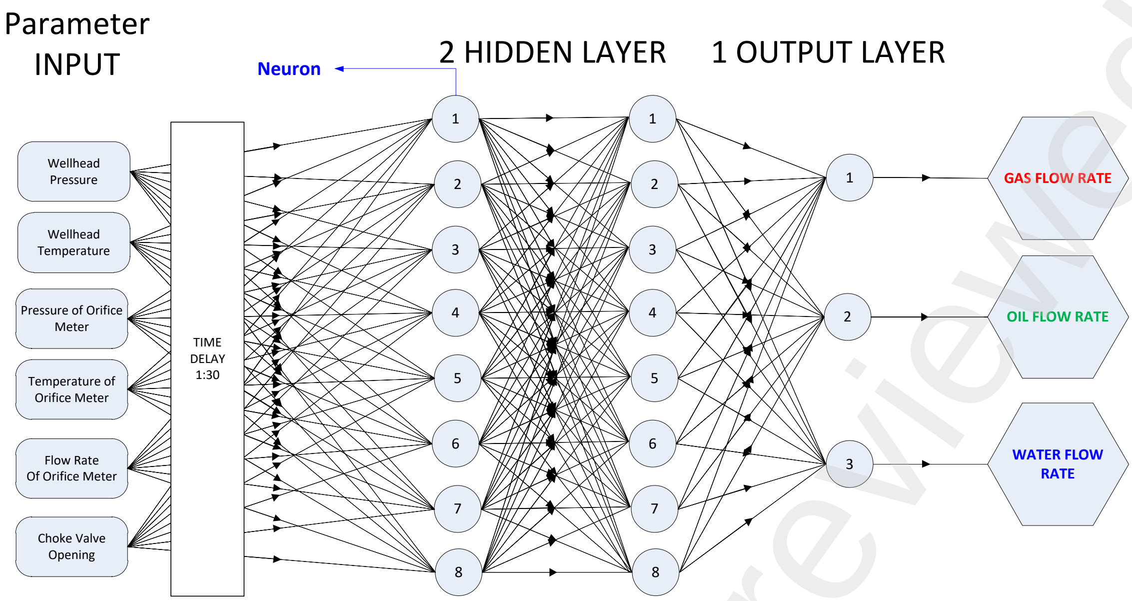

Fig. 6. Schematic of the VMPFM model using TSTD-ANN method

After the verification has been completed and the VMPFM model has met the tolerance limits, the fifth step is carried out, where the VMPFM model is used to predict the output value of gas, oil, and water flow rates. The input data used is data from the last three or four months, from July or August 2021 to October 2021. Then the sixth and final step is the validation of the VMPFM model by comparing the predicted output value of the flow rate from VMPFM to the actual value from well testing measurements by MPFM. When validating the performance of the VMPFM's accuracy against a reference measurement, which in this case is the MPFM, it is necessary to have an error tolerance limit for both measurements. According to the Guidelines for Qualification of Multiphase Metering Systems for Well Testing [29], the terminology of "total probable error" (TPE) is used to obtain the maximum possible error when comparing MPFM measurements against a reference. This approach can be implemented when comparing measurements by the VMPFM against the reference MPFM. The tolerance limit can be calculated using the equation 9 below [29]:

$$TPE = \sqrt{[(EVMPFM^2) + (EMPFM^2)]} \tag{9}$$

Where TPE is *Total Probable Error* in %, EVMPFM is accuracy of VMPFM in %, EMPFM is accuracy of MPFM in %.

Based on the formula above, the tolerance limits error for VMPFM measurement against MPFM can be determined using TPE. The maximum accuracy of MPFM is assumed by +/- 15% for each three phases due to several factors that reduce the uncertainty [30] such as infrequent of sensor maintenance, rapid change of fluid composition, and operating in low pressure beside its accuracy limitation based on manufacturer specification. On the other hand, by assuming that the accuracy performance of VMPFM is comparable to the MPFM accuracy of maximum by +/- 15% relative on each three phases, namely gas flow rate (Qgas), oil flow rate (Qoil), and water flow rate (Qwater), then the tolerance limit error of VMPFM against MPFM in each phase can be calculated by +/- 21% relative according to the calculation in table 1.

Table. 1. Tolerance limit error VMPFM vs MPFM

No	Phase	Accuracy VMPFM (%)	Accuracy MPFM (%)	Tolerance Limit error (%)
1	Qgas	+/- 15 %	+/- 15 %	$\sqrt{(15^2 + 15^2)}$ = +/- 21 %
2	Qoil	+/- 15 %	+/- 15 %	$\sqrt{(15^2 + 15^2)}$ = +/- 21 %
3	Qwater	+/- 15 %	+/- 15 %	$\sqrt{(15^2 + 15^2)}$ = +/- 21 %

If the verification or validation results do not meet the tolerance limit error, a re-check will be performed in the third and sixth steps to resolve the problem. Several methods were carried out, including checking for overfitting, retraining the model, modifying the number of neurons, modifying the number of hidden layers, changing the transfer function, and increasing the amount of training data. The problem that often arises in ANN simulations is overfitting, although problems such as underfitting also often occur. Underfitting is a condition that occurs when the ANN model produces a large enough error because it cannot generalize the correlation between predicted and actual data. Meanwhile, overfitting is an anomaly condition when the error generated during the training stage is expected to be as small as possible, but when the model receives new input data, the resulting error becomes large. This shows that the model only learns from the input data used during training and has not fully learned to generalize the new input data. Several techniques are used to overcome the problem of overfitting, including: (1) repetitive training, (2) Early stopping (Figure 7), and (3) Enlarge the artificial neural network [23,24].

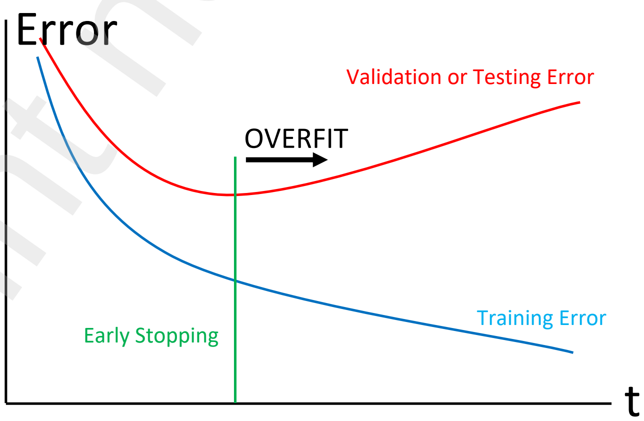

Fig. 7. Illustration of early stopping to prevent overfitting.

4 VMPFM Modelling with Data and Simulation

4.1 Data Analysis

Actual measurement data from well testing of oil and gas wells is used in this study. There are six parameter input data, which include wellhead pressure and wellhead temperature, choke valve opening, and well orifice flow meters of pressure, temperature, and gas flow rate. While there are three parameter target data both for training and for validation of the VMPFM model, which are gas flow rate (Qgas), oil flow rate (Qoil), and water flow rate (Qwater) measured by MPFM. The nine-parameter data can be seen in Table 2. A total of 4367 data samples, which are an average of every five minutes for each parameter data, were retrieved from the DCS database server and subsequently collected over the last two years, starting from May 2020 to October 2021.

The data set will then be divided into two parts. The first data set will be used for training which consists of learning, validating, and testing. The training phase uses data set of first thirteen or fourteen months starting from May 2020 to July or August 2021. The second data set, starting from July or August to October 2021, will be used as a reference for the purpose of validating predictions from the trained VMPFM model. Statistical parameters of those 4367 samples data can be analyzed, such as the average value, maximum value, minimum value, and standard deviation (Table 3). The significant difference between the minimum and maximum values for each parameter indicates that the parameter changes are dynamic. This is reasonable due to the phenomenon of oil and gas wells, which tend to decrease naturally in production due to depleted reserves in the well's reservoir. In addition, there are also interventions carried out in wells with the aim of increasing production, which causes the parameters in the well to fluctuate.

4.2 Simulation and Results

The TSTD-ANN simulation used variance in data input delay time to observe each accuracy performance. There are ten trials of simulation with a variance of delay parameter data input ranging from 20 to 38. The number of parameter data input is six, and the number of parameter data targets is three. The number of hidden layers is set to two, and the number of neurons is set to fifteen. Learning rules use LM, hidden layer activation functions use the sigmoid transfer function, and output layer activation functions use the linear transfer function. The simulation is divided into two stages, which are the training stage and the validation stage. There are 3564 data points for each parameter in the training stage, starting from May 2020 to July 2021, while there are 803 data points for each parameter in the validation stage, starting from August 2021 to July 2021. In the training stage, the learning, validating, and testing configurations are set to 70%, 15%, and 15%, respectively. Early stopping is configured to prevent overfitting by triggering it after six consecutive errors in the validation step.

The verification of performance accuracy in the training stage uses MSE, R, and MAPE. Based on trial and error to get fast simulation, the values of MSE and MAPE shall be less than or equal to 1500 and 65%, respectively. While R value shall be greater than or equal to 0.95. During the validation stage, the prediction of the multiphase flow rate made by the trained model will be compared with the actual measurement made by the MPFM. Based on the TPE calculation, the tolerance limit error should be less than +/- 21% for both measurements. The result of the simulation can be seen in Table 4. Nine out of ten trials' verification of performance accuracy results in the training stage are within tolerance. Most simulations show that the value of MSE is less than 1000, the value of R is greater than 0.95, and the value of MAPE is less than 65% (Fig. 8). In addition, it can be observed that the training duration increases when the parameter input delay time increases (Fig. 9).

Table. 2. Example of nine data parameters used for the modelling of VMPFM

TIME	CHOKE VALVE OPENING	WELL HEAD		FLOWLINE			MPFM		
		P	T	P	T	FLOW	GAS FLOW	OIL FLOW	WATER FLOW
	%	Bar	DegC	Bar	DegC	MMscfd	MMscfd	BPD	BPD
5/15/20 14:00	99.84	41.78	80.46	24.98	71.50	4.96	5.90	524.51	3.92
5/15/20 14:05	99.84	41.81	80.47	24.97	71.54	4.97	5.83	599.31	1.31
5/15/20 14:10	99.84	41.78	80.45	24.86	71.44	4.99	5.89	521.56	4.15
5/15/20 14:15	99.83	41.79	80.46	24.88	71.53	4.95	5.92	545.01	7.00
5/15/20 14:20	99.84	41.81	80.48	24.92	71.55	4.97	5.83	587.64	2.18
5/15/20 14:25	99.84	41.78	80.46	24.98	71.56	4.91	5.85	531.75	5.47
5/15/20 14:30	99.83	41.80	80.46	24.91	71.55	4.96	5.91	500.40	10.02
5/15/20 14:35	99.83	41.81	80.46	24.94	71.55	4.90	5.86	534.36	6.28
5/15/20 14:40	99.84	41.80	80.45	24.94	71.59	5.01	5.86	531.97	3.31
5/15/20 14:45	99.84	41.78	80.45	24.98	71.63	4.97	5.86	563.78	3.28
5/15/20 14:50	99.83	41.82	80.44	24.96	71.64	4.92	5.86	532.63	4.95
5/15/20 14:55	99.84	41.86	80.46	24.91	71.59	4.93	5.84	546.83	3.42
5/15/20 15:00	99.83	41.87	80.47	24.94	71.68	4.99	5.80	588.03	1.26
5/15/20 15:05	99.83	41.79	80.48	24.97	71.64	4.96	5.90	573.49	7.78
5/15/20 15:10	99.84	41.86	80.48	24.96	71.54	4.93	5.85	511.02	1.79
5/15/20 15:15	99.84	41.75	80.48	24.91	71.51	4.93	5.87	544.51	3.58
5/15/20 15:20	99.84	41.86	80.48	24.96	71.52	5.00	5.86	560.05	1.79
5/15/20 15:25	99.84	41.83	80.48	24.99	71.44	4.95	5.86	537.49	2.16
5/15/20 15:30	99.84	41.75	80.49	24.95	71.44	4.93	5.91	532.31	5.84
5/15/20 15:35	99.84	41.85	80.48	25.03	71.41	4.98	5.88	549.27	1.26
5/15/20 15:40	99.84	41.89	80.48	24.98	71.30	4.90	5.87	543.78	2.79
5/15/20 15:45	99.84	41.84	80.48	24.97	71.30	4.96	5.89	487.11	11.31
5/15/20 15:50	99.84	41.81	80.46	25.07	71.45	4.96	5.91	503.06	9.57
5/15/20 15:55	99.83	41.83	80.46	24.99	71.44	4.98	5.82	576.46	1.26
5/15/20 16:00	99.84	41.77	80.48	24.99	71.37	5.03	5.91	519.52	3.79

This shows that the simulation is getting more complex due to the increasing number of delay times. Even in trial 10, the duration of the simulation could reach 11 minutes and 20 seconds with a total of 22 iterations. This could be a consideration since the longer the training simulation for each well, the more impractical it is to be implemented in the field, which requires lots of well testing every day. Trials 1 to 5 show errors that are outside the tolerance limit on the three multi-phases at the validation stage. Meanwhile, starting from the 6th trial onward, the error in the liquid phase starts to close to the tolerance limit even though the simulation duration increases. Based on this graph, trial 6 with a delay time of 30 gives the smallest liquid rate error and gas rate error that are close to the tolerance limit with a short simulation duration. According to the flow chart in the methodology, error checking and accuracy improvement will be carried out using the configuration in trial 6.

Table. 3. Statistical analysis of the parameter data well

Statistic of The Parameter Well									
Parameter	Choke Valve Opening	Wellhead		Orifice Flow Meter			MPFM		
	%	Pressure (Barg)	Temperature (Celcius)	Pressure (Barg)	Temperature (Celcius)	Flow rate (MMSCFD)	Gas Flow rate (MMSCFD)	Oil Flow rate (BBL/D)	Water Flow rate (BBL/D)
Number of sample	4367	4367	4367	4367	4367	4367	4367	4367	4367
Minimum Value	37.19	13.27	55.65	12.49	47.73	2.15	0.78	1.53	0.55
Maximum Value	100.00	41.92	85.99	27.56	84.97	7.39	10.28	902.67	102.86
Standard Deviation	8.67	5.46	4.98	4.50	5.71	0.91	1.86	160.80	18.61
Mean	98.39	23.25	78.37	21.72	75.70	4.16	5.15	249.67	31.08

Table. 4. Result of Simulation TSTD-ANN by Variation of Delay Parameter Input Time

		Trial-1	Trial-2	Trial-3	Trial-4	Trial-5	Trial-6	Trial-7	Trial-8	Trial-9	Trial-10
Training Model VMPFM using Actual Well Data from May 2020 to June 2021	Parameter Input number	6	6	6	6	6	6	6	6	6	6
	Parameter Output number	3	3	3	3	3	3	3	3	3	3
	Neuron Number	15	15	15	15	15	15	15	15	15	15
	Hidden Layer Number	2	2	2	2	2	2	2	2	2	2
	Learning rule	LM	LM	LM	LM	LM	LM	LM	LM	LM	LM
	Delay sampling Number	**20**	**22**	**24**	**26**	**28**	**30**	**32**	**34**	**36**	**38**
	Training Duration (Minutes)	2:35	2:34	2:33	4:35	4:11	5:00	4:51	6:30	6:24	11:20
	MSE	945	895	657	561	508	934	610	530	5378	556
	epoch Number	15	14	12	19	15	16	13	16	13	22
	R	0.97	0.97	0.95	0.97	0.97	0.96	0.97	0.97	0.86	0.97
	MAPE	0.4843	0.4909	0.457	0.444	0.446	0.579	0.419	0.487	0.78	0.485
Validation model VMPFM VS MPFM using Actual Well Data from July 2021 to Oct 2021	Average Discrepancy Qgas (%)	60.2%	96.1%	-23.7%	35.9%	33.1%	**22.4%**	64.3%	49.3%	18.0%	25.7%
	Average Discrepancy Qoil (%)	-24.2%	-62.8%	-25.5%	40.5%	26.4%	**8.5%**	-18.1%	-17.4%	20.6%	11.7%
	Average Discrepancy Qwater (%)	17.8%	19.5%	38.8%	37.1%	34.4%	**1.7%**	3.9%	2.5%	-8.0%	27.9%

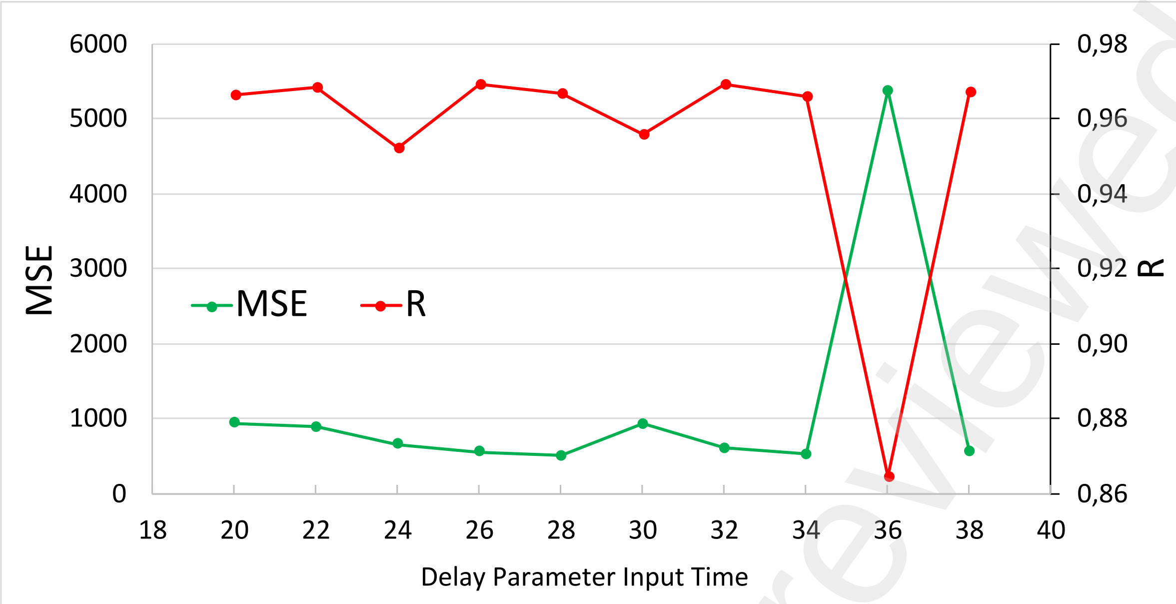

Fig. 8. MSE and R in variation of delay parameter input time

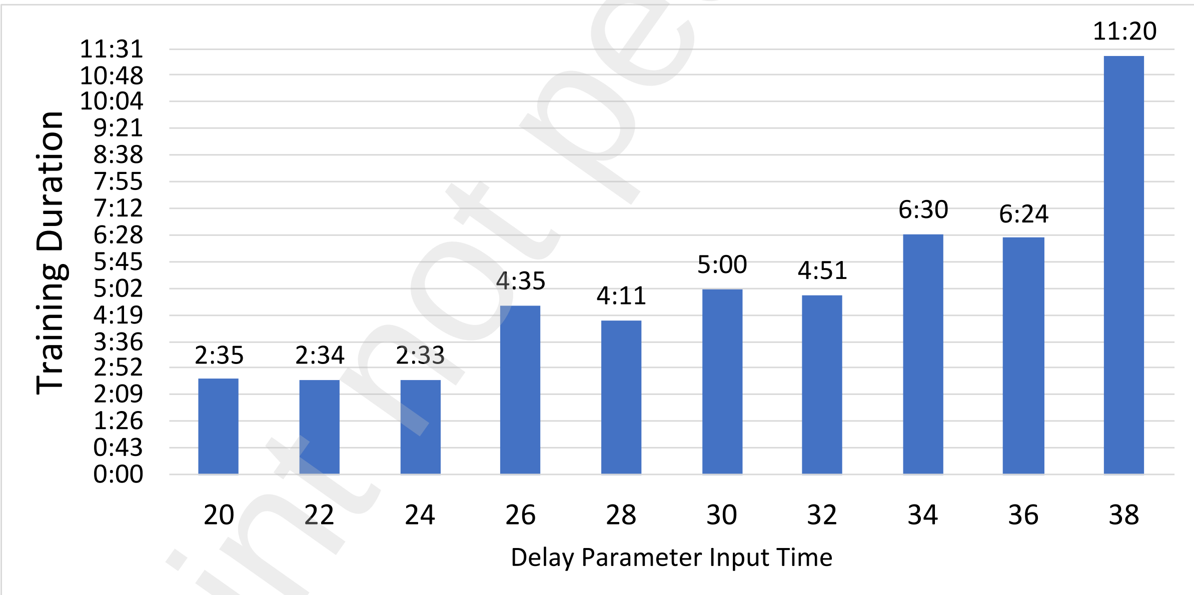

Fig. 9. Delay parameter input vs Training duration (in Minutes)

The method used is repeated testing, varying the number of hidden layers, varying the number of neurons, varying the learning algorithm, and adding the training dataset. The simulation results can be seen in table 5. In the repetitive training simulation, at the training stage, the MSE and R values are within the tolerance limits for both trials. Meanwhile, the MAPE value in the first trial was outside the tolerance limit. While at the validation stage, the two trials showed that the liquid error was within the tolerance limit, while the gas error was still outside the tolerance limit.

In the variation of the number of neurons, the number of neurons used was 11, 13, 17, and 19. At the training stage, the four trials showed accuracy performance that was within the tolerance limits for the three values of MSE, R, and MAPE. While at the validation stage, the error in the gas is still outside the tolerance limit among the four trials.

In the variation of the number of hidden layers, by reducing the number of hidden layers to 1, the simulation results show the accuracy performance of the three MSE, R, and MAPE values at the training stage is within the error tolerance limit. While at the validation stage, the error values obtained from the three phases are still outside the tolerance limit. Furthermore, in the variation of the learning algorithm using SCG, both the accuracy performance during training and during validation show a value that is beyond the tolerance limit.

The final step is to add the dataset at the training stage. The number of data sets per parameter was increased from 3564 to 3710, and the amount of data collected during validation was reduced from 803 to 657. The training stage uses data sets from May 2020 to July 2021, while the validation stage uses data sets from August to October 2021. A total of five trials were carried out, and the simulation results can be seen in table 6. At the training stage, the accuracy performance of the five trials shows MSE, R, and MAPE values that are within the tolerance limits. In addition, the duration of the training is around 5 to 6 minutes to achieve convergence. In Fig. 10, at the training stage of Trial-1, the multiphase flow rate from the simulation results is compared with the actual value, and the results show that the trend of the multiphase flow rate of the model is in line with the trend of the actual value measured by MPFM. R value at the training stage of Trial-1 can be seen in Fig. 11.

At the validation stage, the accuracy performance also shows error values that are within the tolerance limits for the three phases, namely the gas rate, oil rate, and water rate. Trial 1 has the best accuracy performance of the five trials, with an average Qgas discrepancy of 6.0%, a Qoil discrepancy of -16.4%, and a Qwater discrepancy of -2.4%, and a training duration of around 4 minutes and 49 seconds. In Fig. 12, at the validation stage, the multiphase flow rate from the simulation results is compared with the actual value measured by MPFM, and the results show that the simulation results is also in line with the trend of the actual value measured by MPFM.

As for Fig. 13, it shows that the cumulative flow rate values from the simulation results were compared to the actual measurement by MPFM, and the results for the three phases show very close figures for the final cumulative flow rate for each phase. According to API Recommended Practice 86 reference [31], a gas volume fraction (GVF) chart for errors needs to be created to see the correlation of errors on the GVF. GVF is the gas volume flow rate, relative to the multiphase volume flow rate, at the pressure and temperature prevailing in that section, where the GVF is normally expressed as a fraction or percentage [32]. This can be seen in figs. 14–16, where in the GVF range of 99.3–99.7%, the discrepancy values of the two measurements show close differences, while the range outside those range is quite scattered.

Table. 5. Result of Simulation TSTD-ANN by repetitive training, variation of hidden layer, variation of neuron number, and variation of learning rule.

Simulation Model VMPFM by Variation of Hidden Layer Number, Neuron Number, Learning Rule, and Retraining

		TRIAL RETRAINING		TRIAL Variation of Neuron Number				Trial Variation Hidden Layer Number		TRIAL Variation Learning Rule
Training Model VMPFM using Actual Well Data from May 2020 to June 2021	Parameter Input number	6	6	6	6	6	6	6	6	6
	Parameter Output number	3	3	3	3	3	3	3	3	3
	Neuron Number	15	15	11	13	17	19	15	15	15
	Hidden Layer Number	2	2	2	2	2	2	1	3	2
	Learning rule	LM	LM	LM	LM	LM	LM	LM	LM	SCG
	Delay sampling Number	30	30	30	30	30	30	30	30	30
	Training Duration (Minutes)	9:58	6:21	3:50	4:33	5:17	7:30	3:34	8:59	1:16
	MSE	1300	1008	740	731	720	805	990	603	2060
	epoch Number	32	19	22	19	12	13	14	21	50
	R	0.96	0.96	0.97	0.97	0.97	0.97	0.96	0.97	0.95
	MAPE	66.6%	59.9%	50.1%	43.5%	48.1%	46.7%	51.7%	51.3%	205.1%
Validation model VMPFM VS MPFM using Actual Well Data from July 2021 to Oct 2021	Average Discrepancy Qgas (%)	31.3%	31.0%	34.7%	-47.0%	81.5%	-45.6%	-47.0%	11.1%	439.0%
	Average Discrepancy Qoil (%)	-13.1%	-5.6%	20.2%	31.6%	46.5%	-2.8%	-61.6%	-38.1%	15.0%
	Average Discrepancy Qwater (%)	0.5%	-0.6%	5.2%	16.2%	37.4%	3.5%	-40.8%	-21.3%	45.2%

Table. 6. Result of Simulation TSTD-ANN by adding dataset of training.

	Sequence	Trial-1	Trial-2	Trial-3	Trial-4	Trial-5
Training Model VMPFM using Actual Well Data from May 2020 to July 2021	Parameter Input number	6	6	6	6	6
	Parameter Output number	3	3	3	3	3
	Neuron Number	15	15	15	15	15
	Hidden Layer Number	2	2	2	2	2
	Learning rule	LM	LM	LM	LM	LM
	Delay sampling Number	30	30	30	30	30
	Training Duration (Minutes)	4:49	5:46	6:38	6:29	5:13
	MSE	630	367	757	862	911
	epoch Number	14	17	20	17	15
	R	0.97	0.97	0.96	0.97	0.95
	MAPE	45%	40%	53%	43%	65%
Validation model VMPFM VS MPFM using Actual Well Data from Aug 2021 to Oct 2021	Average Discrepancy Qgas (%)	**6.0%**	**-10.3%**	**12.9%**	**9.3%**	**11.3%**
	Average Discrepancy Qoil (%)	**-16.4%**	**17.4%**	**-13.8%**	**15.6%**	**19.9%**
	Average Discrepancy Qwater (%)	**-2.4%**	**17.6%**	**9.4%**	**-2.9%**	**16.1%**

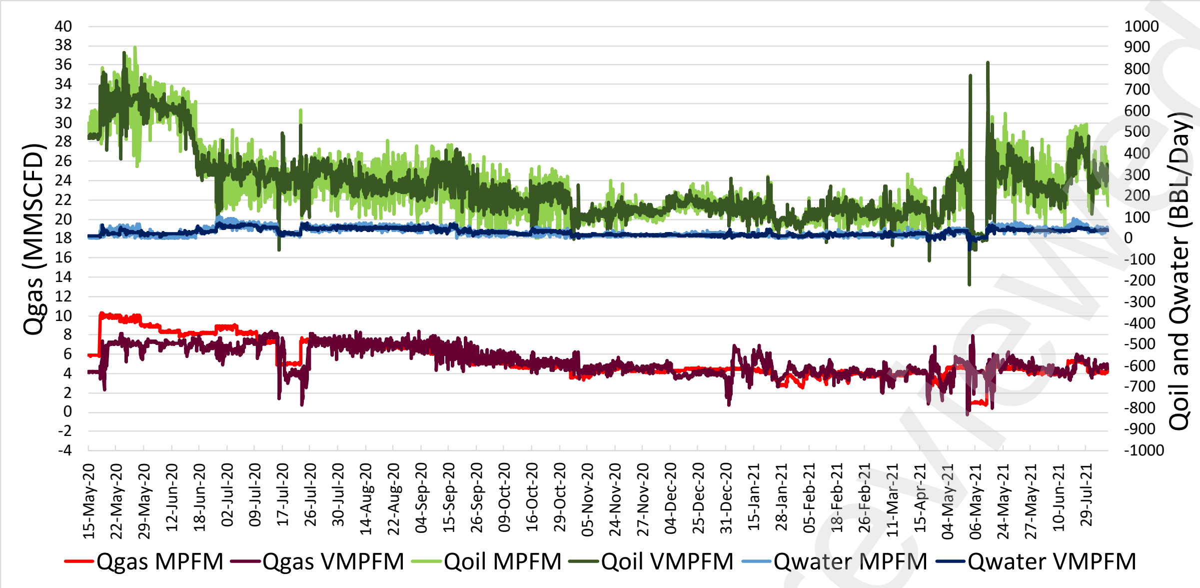

Fig. 10. Multiphase Flow rate of VMPFM VS MPFM in training stage of trial-1

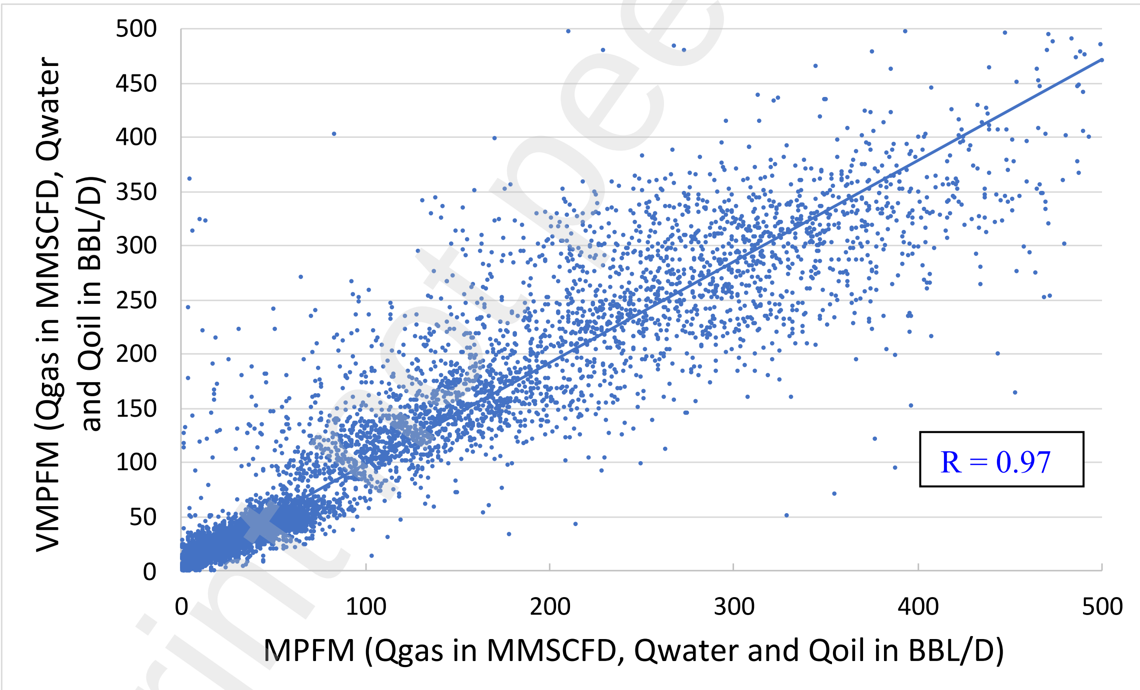

Fig. 11. R Value in training stage of trial-1

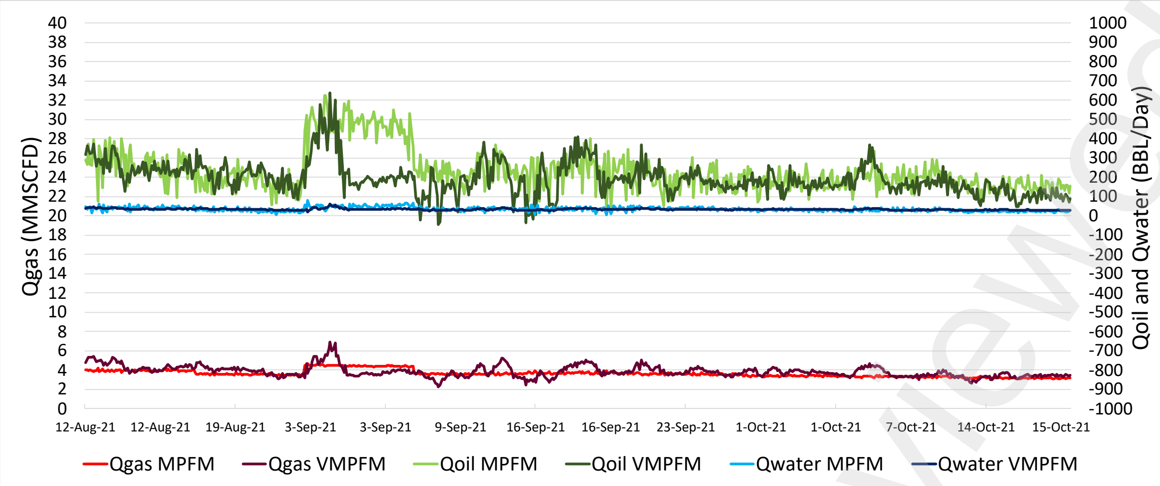

Fig. 12. Multiphase Flow rate of VMPFM VS MPFM in Validation stage of trial-1

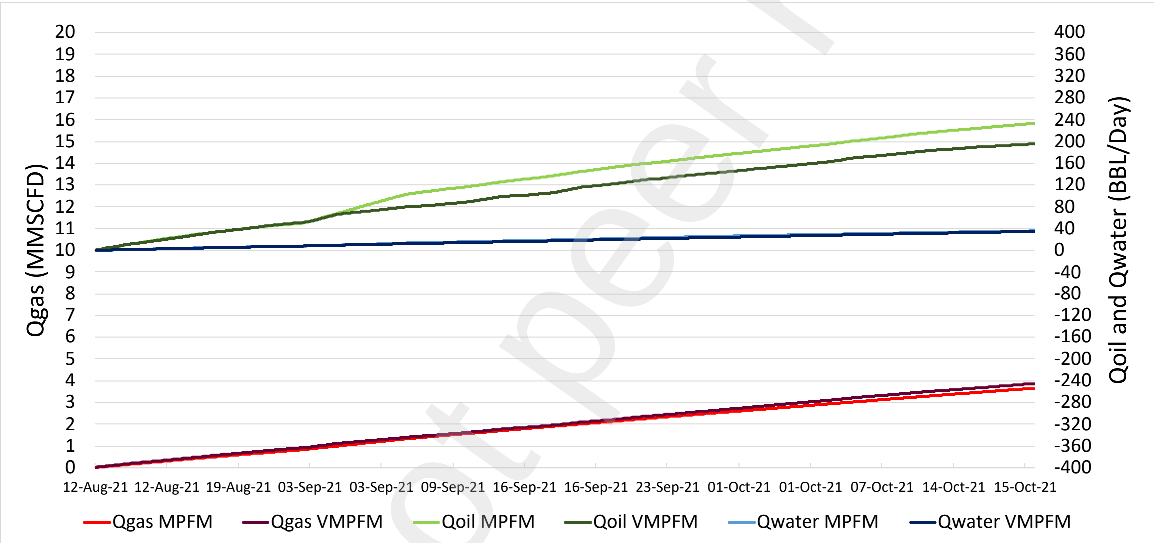

Fig. 13. Multiphase cumulative flow rate of VMPFM VS MPFM in validation stage of trial-1

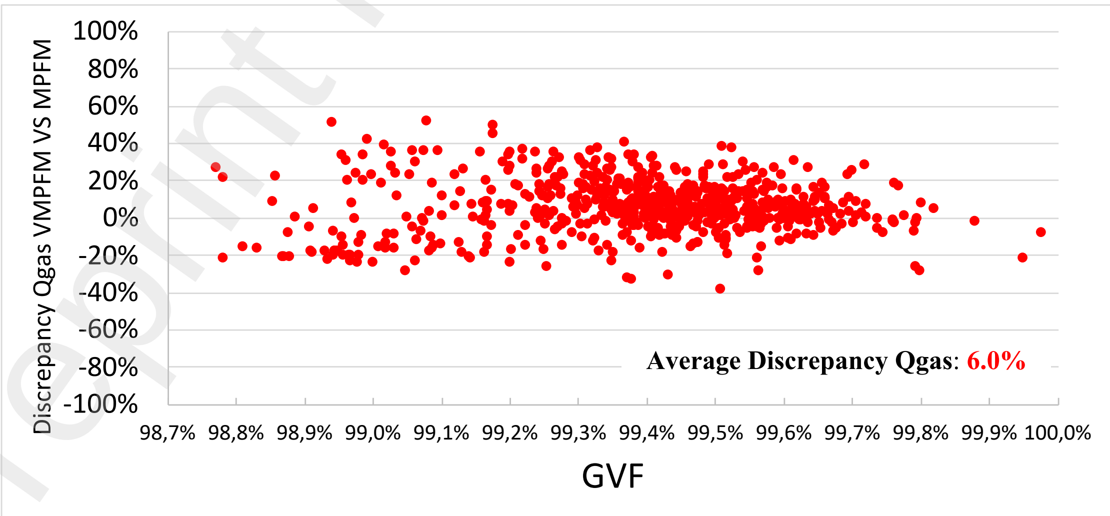

Fig. 14. Discrepancy Qgas of VMPFM against MPFM Vs GVF in validation stage of trial-1

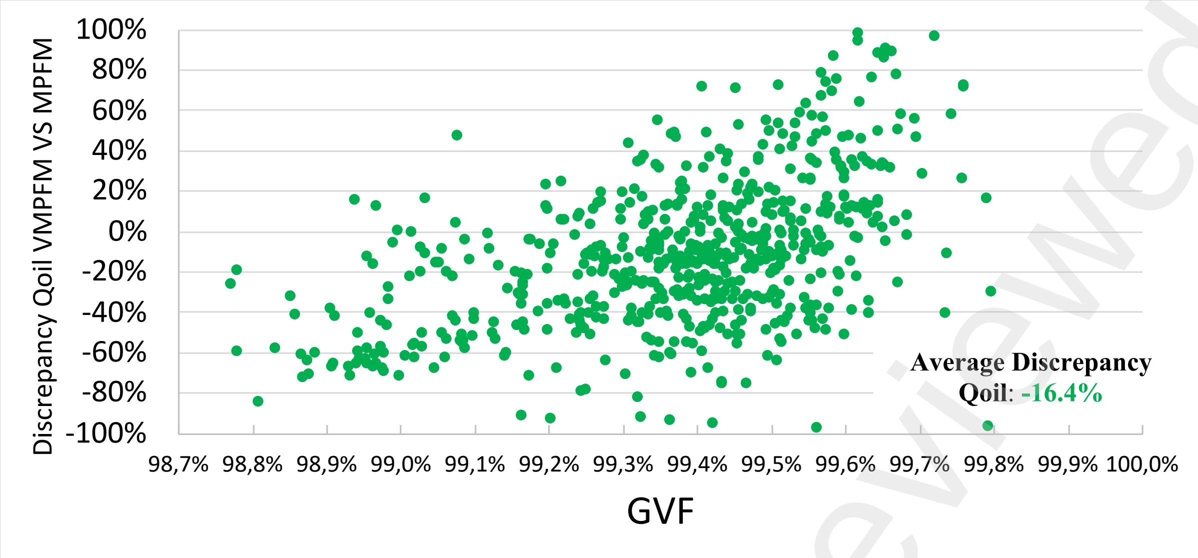

Fig. 15. Discrepancy Qoil of VMPFM against MPFM Vs GVF in validation stage of trial-1

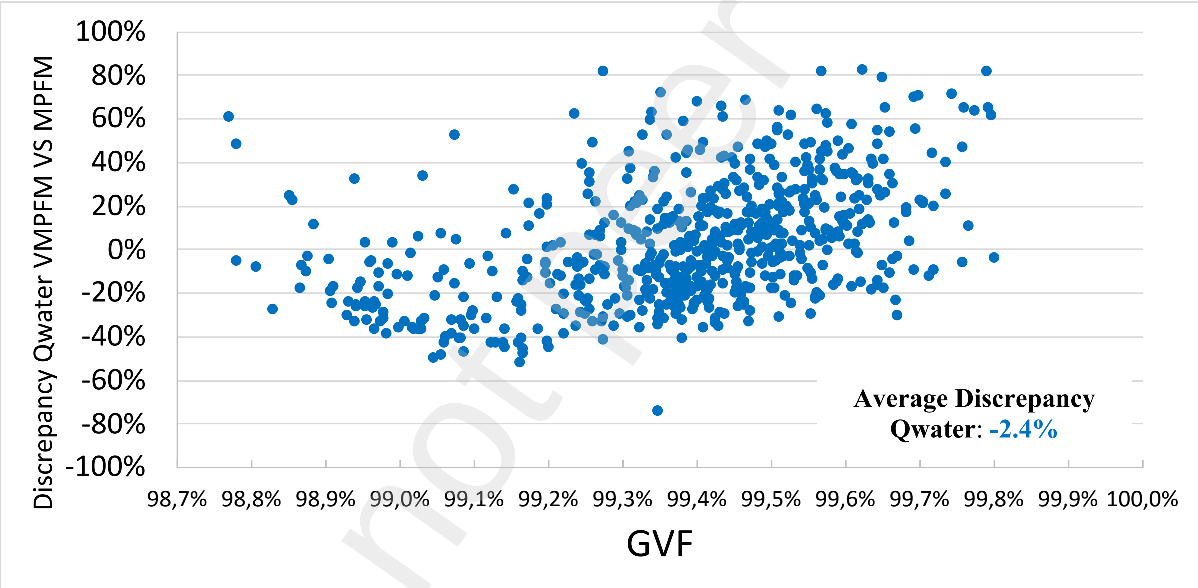

Fig. 16. Discrepancy Qwater of VMPFM against MPFM Vs GVF in validation stage of trial-1

5 Discussion

In this study, a time series time delay artificial neural network (TSTD-ANN) and the utilization of data measurement from existing well orifice flow meter has been used in the development of a virtual multiphase flow meter. The model of VMPFM is validated by the actual measurement of MPFM during well testing in Mahakam Block, East Kalimantan Province, Indonesia. From May 2020 to October 2021, total actual data of around 4367 for each of the nine parameters (input and target) was used for training and validation. The model is trained until the MSE, R, and MAPE fall within the tolerance limits. Early stopping is used to prevent overfitting, and a configuration of six consecutive errors will stop the simulation during the validation check. The Levenberg-Marquardt learning algorithm is set as the learning rule. Linear activation and sigmoid activation were used in the hidden and output layers, respectively.

Among ten trials with variance of parameter input delay time, the configurations of trial-6 with 30 delay time as well as configuration as refer to previous research by 15 number neurons [15], 2 hidden layers [14], The Levenberg-Marquardt learning rules [12, 15,14], and 70%-15%-15% of learning-validation-testing [14] deliver the most accurate and fast simulation, even though it fails to achieve the target tolerance limit error. Another fact from trial-10 can be inferred is that the greater the amount of time delay, the longer the simulation takes. This will be a concern because of the need in the oil and gas industry to test dozens or even hundreds of wells every day.

With unsatisfactory results, attempts to increase accuracy have been made by repeating training simulations, changing the number of hidden layers, changing the number of neurons, and changing the learning method. Even if certain references [23,24] have demonstrated the efficiency of this strategy to improve the model performance, it fails to meet the target accuracy when the error values acquired from the three phases in the validation stage are still outside the tolerance limit.

Finally, the accuracy improved in the last try after training dataset addition, and it was demonstrated by the execution of 5 simulation trials that both verification in training phase and validation phase are within limit tolerance. The MSE, R, and MAPE values are within the allowable tolerance (MSE $\leq$ 1500; R $\geq$ 0.95; MAPE $\leq$ 65%) after the validation of the five training phase trials with the configuration of 30 parameter input delay time and additional training dataset. The five trials in the validation phase demonstrate that, with training time of less than seven minutes, the average discrepancy of multiphase flow rate prediction is less than +/- 21% compared with actual MPFM measurement. Trial-1 of the five simulation trials predicts the multiphase flow rate with the highest degree of accuracy, with average discrepancy of 6.0% for Qgas, -16.4% for Qoil, and -2.4% for Qwater. Additionally, this study demonstrates that three phases of flow rates, rather than just one, can be predicted with tolerable accuracy utilizing measurement data from an existing well orifice meter and the TSTD-ANN approach [19,20].

6 Conclusion and Recommendation

The paper proposed a VMPFM model using a time series-time delay artificial neural network technique in predicting the multiphase flow rate accurately with the best average discrepancy of Qgas (6.0%), Qoil (-16.4%), and Qwater (-2.4%) compared with actual measurement by MPFM. The training of the VMPFM model, which takes less than 7 minutes and has acceptable values for MSE, R, and MAPE, demonstrates that this method is reliable enough to be used in the oil and gas industries, which often require conducting dozens of individual well tests in their daily activities.

The utilization of data measurement of existing well orifice meter combined with data measurement from choke valve and well head as parameter data input of the network has proven effective to improve the accuracy of the VMPFM model. In addition, the greater the number of data used in training phase determines the accuracy performance of the VMPFM model. However, concerning that this study only uses limited well reference data, it is recommended to implement this VMPFM model on other wells in different fields to validate its performance accuracy during well testing.

7 Acknowledgements

The paper is supported by The Research, Community Service, and Innovation Institut Teknologi Bandung, Indonesia 2022. The authors would like to thank for the flow measurement

data of Mahakam Block in Indonesia's east Kalimantan used in the research.

8 Declaration of competing interest

The author declares that he has not any conflict of interest.

Reference.

[1] Falcone, G. , Hewitt, G. , & Alimonti, C. (2009). Multiphase flow metering: principles and applications : 54. Elsevier

[2] T. A. AL-Qutami, R. Ibrahim, I. Ismail, and M. A. Ishak, "Virtual multiphase flow metering using diverse neural network ensemble and adaptive simulated annealing," Expert Syst. Appl., vol. 93, pp. 72–85, 2018, doi: 10.1016/j.eswa.2017.10.014.

[3] Chaves, G., & Engebretsen, S. (2022). Virtual Flow Metering as a digital solution to production management. 2016, 4–7.

[4] Bikmukhametov, T., & Jäschke, J. (2020). First Principles and Machine Learning Virtual Flow Metering: A Literature Review. Journal of Petroleum Science and Engineering,184(September2019),106487.https://doi.org/10.1016/j.petrol.2019.106487

[5] Al-Abduljabbar, A., Gamal, H., & Elkatatny, S. (2020). Application of artificial neural network to predict the rate of penetration for S-shape well profile. Arabian Journal of Geosciences, 13(16). https://doi.org/10.1007/s12517-020-05821-w.

[6] Elgibaly, A. A., Ghareeb, M., Kamel, S., & El-Sayed El-Bassiouny, M. (2021). Prediction of gas-lift performance using neural network analysis. AIMS Energy, 9(2), 355–378. https://doi.org/10.3934/energy.2021019

[7] Alkinani, H. H., Al-Hameedi, A. T. T., & Dunn-Norman, S. (2021). Data-driven recurrent neural network model to predict the rate of penetration: Upstream Oil and Gas Technology. Upstream Oil and Gas Technology, 7(March), 100047. https://doi.org/10.1016/j.upstre.2021.100047

[8] Al-Naser, M., Elshafei, M., & Al-Sarkhi, A. (2016). Artificial neural network application for multiphase flow patterns detection: A new approach. Journal of Petroleum Science and Engineering, 145, 548–564. https://doi.org/10.1016/j.petrol.2016.06.029

[9] Arjun, K. S., & Aneesh, K. (2015). Modelling studies by application of artificial neural network using matlab. Journal of Engineering Science and Technology, 10(11), 1477–1486.

[10] C. Sheppard, D. Russell, The application of artificial neural networks to non-intrusive multi-phase metering, Contr. Eng. Pract. 1 (2) (1993) 299–304.

[11] S. Elmabrouk, E. Shirif, and R. Mayorga, "Artificial neural network modeling for the prediction of oil production," Pet. Sci. Technol., vol. 32, no. 9, pp. 1123–1130, 2014, doi: 10.1080/10916466.2011.605093.

[12] M. Z. Hasanvand, "Energy Sources , Part A : Recovery , Utilization , and Environmental Effects Predicting Oil Flow Rate due to Multiphase Flow Meter by Using an Artificial Neural Network," no. March 2015, 2017, doi: 10.1080/15567036.2011.590865.

[13] L. Muradkhanli, "Neural Networks for Prediction of Oil Production," IFAC-PapersOnLine, vol. 51, no. 30, pp. 415–417, 2018, doi: 10.1016/j.ifacol.2018.11.339.

[14] B. Bahrami, S. Mohsenpour, H. R. Shamshiri Noghabi, N. Hemmati, and A. Tabzar, "Estimation of flow rates of individual phases in an oil-gas-water multiphase flow system using neural network approach and pressure signal analysis," Flow Meas. Instrum., vol. 66, no. December 2018, pp. 28–36, 2019, doi: 10.1016/j.flowmeasinst.2019.01.018.

[15] R. Abdel Azim, "Prediction of multiphase flow rate for artificially flowing wells using rigorous artificial neural network technique," Flow Meas. Instrum., vol. 76, no. June, p. 101835, 2020, doi: 10.1016/j.flowmeasinst.2020.101835.

[16] T. A. Al-Qutami, R. Ibrahim, and I. Ismail, "Hybrid neural network and regression tree ensemble pruned by simulated annealing for virtual flow metering application," Proc. 2017 IEEE Int. Conf. Signal Image Process. Appl. ICSIPA 2017, pp. 304–309, 2017, doi: 10.1109/ICSIPA.2017.8120626.

[17] N. Andrianov, "A Machine Learning Approach for Virtual Flow Metering and Forecasting," IFAC-PapersOnLine, vol. 51, no. 8, pp. 191–196, 2018, doi: 10.1016/j.ifacol.2018.06.376.

[18] M. A. Ahmadi, M. Ebadi, A. Shokrollahi, and S. M. Javad Majidi, "Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir," Appl. Soft Comput. J., vol. 13, no. 2, pp. 1085–1098, 2013, doi: 10.1016/j.asoc.2012.10.009.

[19] H. Ghorbani et al., "Prediction of oil flow rate through an orifice flow meter: Artificial intelligence alternatives compared," Petroleum, vol. 6, no. 4, pp. 404–414, 2020, doi: 10.1016/j.petlm.2018.09.003.

[20] Farsi, M., Shojaei Barjouei, H., Wood, D. A., Ghorbani, H., Mohamadian, N., Davoodi, S., Reza Nasriani, H., & Ahmadi Alvar, M. (2021). Prediction of oil flow rate through orifice flow meters: Optimized machine-learning techniques. Measurement: Journal of the International Measurement Confederation, 174. https://doi.org/10.1016/j.measurement.2020.108943

[21] Grimstad, B., Hotvedt, M., Sandnes, A. T., Kolbjørnsen, O., & Imsland, L. S. (2021). Bayesian neural networks for virtual flow metering: An empirical study. Applied Soft Computing, 112, 107776. https://doi.org/10.1016/j.asoc.2021.107776

[22] Choubineh, A., Ghorbani, H., Wood, D. A., Robab Moosavi, S., Khalafi, E., & Sadatshojaei, E. (2017). Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning based optimization. Fuel, 207, 547–560. https://doi.org/10.1016/j.fuel.2017.06.131.

[23] Hagan, M. T. , Demuth, H. B. , Beale, M. H. , & De Jesús, O. (1996). Neural network design : 20. PWS publishing company Boston .

[24] H. B. D. Beale Martin T. Hagan, Mark Hudson, "Neural Network Toolbox TM 6 User ' s Guide," Network, vol. 9, no. 4, pp. 259–265, 2000.

[25] Andries P. Engelbrecht. (2007). Computational Intelligence An Introduction, second edition : 54. John Wiley & Sons,

[26] C. C. Aggarwal, Neural Networks and Deep Learning. 2018.

[27] Levenberg, K. (1944) A Method for the Solution of Certain Problems in Least Squares. Quarterly of Applied Mathematics, 2, 164-168. https://doi.org/10.1090/qam/10666.

[28] P. Panja, W. Jia, and B. McPherson, "Prediction of well performance in SACROC field

using stacked Long Short-Term Memory (LSTM) network," Expert Syst. Appl., vol. 205, no. May, p. 117670, 2022, doi: 10.1016/j.eswa.2022.117670.

[29] J. Williamson, "QUALIFICATION OF MULTIPHASE METERING State of Alaska Alaska Oil & Gas Conservation Commission Guidelines for Qualification of Multiphase Metering Systems for Well Testing," 2004.

[30] Folgerø, K., Soldal, E. L., Kocbach, J., Frøysa, K. E., Kleppe, K., & Åbro, E. (2013). Uncertainty analysis of multiphase flow meters used for allocation measurements: Field experiences and future challenges. 31st International North Sea Flow Measurement Workshop, NSFMW 2013, October, 1–20.

[31] "APl Recommended Practice for Measurement of Multiphase Flow, API Recommended Practice 86, First Edition, September 2005

[32] Corneliussen, S. , Couput, J.-P. , Dahl, E. , Dykesteen, E. , Frøysa, K.-E. , Malde, E. , et al. (2005). Handbook of multiphase flow metering. Norwegian Society for Oil and Gas Measurement (NFOGM), Revision, 2.