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Fuel

Robust hybrid machine learning algorithms for gas flow rates prediction through wellhead chokes in gas condensate fields --Manuscript Draft--

Manuscript Number:	JFUE-D-21-01682R3
Article Type:	Research Paper
Keywords:	Gas flow rate, multi-hidden layer extreme learning machine, hybrid machine learning algorithms; least squares support vector machine, wellhead choke.
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Abstract:	<p>Condensate reservoirs are the most challenging hydrocarbon reservoirs in the world. The behavior of condensate gas reservoirs regarding pressure and temperature variation is unique. Adjusting fluid flow rate through wellhead chokes of condensate gas wells is critical and challenging for reservoir management. Predicting this vital parameter is a big step for the development of condensate gas fields. In this study, a novel machine learning approach is developed to predict gas flow rate (Q_g) from six input variables: temperature (T); upstream pressure (P_u); downstream pressure (P_d); gas gravity (γ_g); choke diameter (D_{64}) and gas-liquid ratio (GLR). Due to the absence of accurate recombination methods for determining Q_g, machine learning methods offer a functional alternative approach. Four hybrid machine learning (HLM) algorithms are developed by integrating multiple extreme learning machine (MELM) and least squares support vector machine (LSSVM) with two optimization algorithms, the genetic algorithm (GA) and the particle swarm optimizer (PSO). The evaluation conducted on prediction performance and accuracy of the four HLM models developed indicates that the MELM-PSO model has the highest Q_g prediction accuracy achieving a root mean squared error (RMSE) of 2.8639 MScf/Day and a coefficient of determination (R^2) 0.9778 for a dataset of 1009 data records compiled from gas-condensate fields around Iran. Comparison of the prediction performance of the HLM models developed with those of the previous empirical equations and artificial intelligence models reveals that the novel MELM-PSO model presents superior prediction efficiency and higher computational accuracy. Moreover, the Spearman correlation coefficient analysis performed demonstrates that D_{64} and GLR are the most influential variables in the gas flow rate for the large dataset evaluated in this study.</p>

Robust hybrid machine learning algorithms for gas flow rates prediction through wellhead chokes in gas condensate fields

Highlights

- 1009 record data of from the Iranian condensate fields (Marun-Khami, Aghajari-Khami and Ahvaz-Khami).
- New hybrid machine learning technique accurately predicts gas flow rate through wellhead choke in gas condensate reservoirs.
- MELM-PSO model constructs the most accurate condensate gas flow rate predictions.
- Choke size (D_{64}), downstream pressure (P_d) and gas liquid ratio (GLR) have the greatest influence.

Robust hybrid machine learning algorithms for gas flow rates prediction through wellhead chokes in gas condensate fields

By

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Robust hybrid machine learning algorithms for gas flow rates prediction through wellhead chokes in gas condensate fields

Abstract

Condensate reservoirs are the most challenging hydrocarbon reservoirs in the world. The behavior of condensate gas reservoirs regarding pressure and temperature variation is unique. Adjusting fluid flow rate through wellhead chokes of condensate gas wells is critical and challenging for reservoir management. Predicting this vital parameter is a big step for the development of condensate gas fields. In this study, a novel machine learning approach is developed to predict gas flow rate (Q_g) from six input variables: temperature (T); upstream pressure (P_u); downstream pressure (P_d); gas gravity (γ_g); choke diameter (D_{64}) and gas-liquid ratio (GLR). Due to the absence of accurate recombination methods for determining Q_g , machine learning methods offer a functional alternative approach. Four hybrid machine learning (HLM) algorithms are developed by integrating multiple extreme learning machine (MELM) and least squares support vector machine (LSSVM) with two optimization algorithms, the genetic algorithm (GA) and the particle swarm optimizer (PSO). The evaluation conducted on prediction performance and accuracy of the four HLM models developed indicates that the MELM-PSO model has the highest Q_g prediction accuracy achieving a root mean squared error (RMSE) of 2.8639 MScf/Day and a coefficient of determination (R^2) 0.9778 for a dataset of 1009 data records compiled from gas-condensate fields around Iran. Comparison of the prediction performance of the HLM models developed with those of the previous empirical equations and artificial intelligence models reveals that the novel MELM-PSO model presents superior

prediction efficiency and higher computational accuracy. Moreover, the Spearman correlation coefficient analysis performed demonstrates that D_{64} and GLR are the most influential variables in the gas flow rate for the large dataset evaluated in this study.

Keywords: Gas flow rate, multi-hidden layer extreme learning machine, hybrid machine learning algorithms; least squares support vector machine, wellhead choke.

1. Introduction

Hydrocarbon fuels are still recognized worldwide as the driving force and strategic energy to develop leading economic and industrial goals [1-3]. A sustainable production approach from hydrocarbon reservoirs is an essential production management policy that enables upstream companies to exploit hydrocarbon reservoirs efficiently [4]. Regardless of the economic perspective, controlling the production rate by wellhead chokes is the most important management lever for optimizing the production process. Increasing the production rate without involving engineering concerns adversely affects wells' productivity and shortens their production life [5]. Such problems will be exacerbated, especially in unconventional gas reservoirs with tight carbonated structure and very low permeability [6]. The unique phase behavior of condensate gas makes the production rate control techniques even more challenging and vital in such reservoirs. [7]. In condensate reservoirs, the production rate declines significantly due to the accumulation of unproducible liquid in the near-wellbore region [8]. The reservoir fluid in the regions far from the wellbore is a combination of rich gas and non-moveable connate water. At the early production stage, the pressure drops below the dew point near the wellbore region, and the rich gas is converted into condensate. This isothermal

condensation is known as retrograde condensation [9]. The accumulation of valuable condensate droplets around the wellbore, also known as the condensate bank/ring, has not yet reached critical saturation for portability, resulting in a positive skin factor [10]. Production from gas condensate reservoirs requires meticulous planning and management [11]. Scheduled production plans for sale and export contracts of gas and gas condensate productive [12] require continuous production at the desired rate. Any disruption to the production process may damage economic obligations. Therefore, accurate control and management of production rates and pressure drop through production wells are essential to implement sustainable production programs from condensate reservoirs. By understanding the importance of preserving and sustainable production from gas condensate resources, the position and credibility of efficient tools for control and handling of this vital goal become clearer. Wellhead chokes are a very cost-effective and efficient tool for measuring and controlling multiphase flow rates at an optimum level [13]. Accurate measurement of multiphase flow is one of the concerns of production engineers [14]. The values determined in these measurements are the basic input parameters for calculation in many reservoir performance relationships. Determination of multiphase flow rate is crucial in planning and adopting correct measures and reforms in production policies commensurate with the reservoir's performance during operation [15]. The back pressure applying by wellhead chokes has several advantages, such as stabilizing the multiphase flow rate [16], preventing further pressure drop at the bottom hole section and condensate drop out, avoiding to create the skin factor due to pressure drop, and preventing water coning in gas condensate reservoirs [17, 18]. Numerous experimental and theoretical relationships have been introduced to estimate the multiphase flow rate through wellhead chokes. In most of them, the basis of flow calculations depends on the

pressure difference between the upstream and downstream instruments [19-21]. One of the most popular computational models proposed belongs to Gilbert (1954), which has been widely used to calculate the liquids flow rate through the wellhead choke and in recent years has been adapted for data from different regions (shown in Eq. (1)) [22-26]:

$$Q_{liq} = M \frac{P_{wh} D_{64}^O}{GLR^I} \quad (1)$$

Where Q_{liq} is the rate of liquids production (STB/D), P_{wh} is the wellhead pressure (psi), D_{64} is the choke size (1/64 inch), GLR is the gas to liquid ratio (SCF/STB), and M, I, O are experimental coefficients calculated where sufficient data is available for specific reservoir systems.

Osman and Dokla 1990 used a dataset from gas condensate wells in the Middle East region to develop an empirical relationship for calculating the flow through the wellhead chokes [27]. They adapted the Gilbert equation in three modified forms by changing the pressure parameters (replacing the upstream pressure with the pressure drop across the choke) for the wells' data in gas condensate reservoirs. Guo et al. 2002 evaluated data from 239 condensate gas wells with Sachdeva's multiphase choke flow equation and compared the results with field measurements. After receiving the under-estimated performance feedback from this model, they could adapt it using different choke discharge coefficients (CD) to obtain less computational error [28]. Al-Attar 2008 developed an empirical equation to describe a sub-critical flow model in gas condensate wellhead chokes ranging from 24/64 to 128/64 inches for different choke sizes [29]. Nasriani and Kalantariasl (2019) also presented a tuned equation derived from the Gilbert basic equation to measure flow rate in sub-critical flow regime based on data collected from 50 wells in some gas condensate reservoirs

in southern Iran [30]. Seidi and Sayahi (2015), by adapting Gilbert's basic equation using the genetic algorithm and nonlinear regression methods and applying them to 67 datasets gathered from different gas condensate fields, proposed an optimized model for estimating the condensate gas flow rate [31]. The equations presented by these researchers are summarized in Table 1.

Recently, some researchers strived to solve many oil, gas and geological hydrogen storage [32-36]. However, data science has provided a new way to move from conventional computing systems to faster, more accurate, and cost-effective computing methods. Today, new machine learning techniques are efficient tools for optimization and sophisticated computing that reduce operating costs and improve system performance. Extensive research has been conducted in recent years on the application of intelligent machine learning methods in various sectors of the upstream oil and gas industry, such as desalting system analysis [37], hydrocarbon phase behavior prediction [38-42], determination of oil and gas flow through orifice [43-46] and determination of flow rate through wellhead choke [18, 47-53]. Predicting multiphase flow rate from wellhead chokes is the subject of other studies on machine learning application in flow measurement concepts. Table 2 summarizes some of the recently published research on these smart models' performance in this field.

As shown in Table 2, in recent years, intelligent machine learning models for accurately estimating the flow rate of hydrocarbon fluids passing through wellhead chokes have been inexpensive, fast, and accurate solutions for calculating the production flow of hydrocarbon fluids. Machine learning models require a large and extensive range of data set to create a comprehensive and more accurate model. There is still a shortage of model construction by vast data sets specifically structured to predict gas flow rates.

Table 1 provides a comparison of previous empirical relationships, and Table 2 shows the results of intelligent methods proposed in previous studies. It is worth noting that the methods proposed in this paper are compared with those empirical methods in previous studies that presented better performance. In addition, as shown in Table 2, a limited number of studies have been performed on the gas flow rate prediction in gas & gas condensate reservoirs. As a result, this research, based on a database made of more than 1009 data records, has endeavored to develop novel models for gas flow rate prediction (MELM with PSO/GA optimizer) with minimized RMSE. The model developed employs six input variables, including temperature (T), upstream pressure (P_u), downstream pressure (P_d), gas gravity (γ_g), choke diameter (D_{64}), and gas-liquid ratio (GLR) to accurately predict gas flow rate from wellhead chock. Moreover, to create the best possible prediction performance and accuracy as well as to avoid overfitting, several control measures are applied in the present study.

Table 1. Empirical equations proposed by some researchers to determine the flow rate of condensate gas through wells.

Year	Authors / Reference	Formula	Dataset	Units	Coefficient	R ²	Error Functions
1990	Osman & Dokla [27]	$Q_g = a * \frac{P_u^b * D_{64}^c}{LGR^d}$	87 data points	Q _g : MScf/Day, P _u : Psia, D ₆₄ : inch, LGR: STB/MScf	a= 0.00130, b=1, c= 1.8298, d= 0.5598	-	Best result: AAPD%= 10.64
2008	Al-Attar [29]	$Q_g = a * \Delta p^b * D_{64}^c * GLR^d$	97 data points	Q _g : MMScf/Day, Δp: Psi, D ₆₄ : inch, LGR: STB/MScf	a= 3.37230e-5, b=1, c= 1.15537, d= 0.84695	Best result: 0.9521	Best result: AAPD%= 7.144
2015	Seidi and Sayahi [31]	$Q_g = a * \frac{\Delta p^b * D_{64}^c}{LGR^d}$	106 data points	Q _g : MMScf/Day, Δp: Psi, D ₆₄ : inch, LGR: STB/MMScf	a= 0.015, b=0.65, c= 1.27, d= 0.4	Best result: 0.9161	Best result: APD%= 23.93
2017	Ghorbani et al. [18]	$Q_g = a D_{64}^b \left(\frac{P_u}{14.7} \right)^c \sqrt{\left(\frac{1}{\gamma_g T} \right)^d \left[\left(\frac{P_d}{P_u} \right)^e - \left(\frac{P_d}{P_u} \right)^f \right]}$	92 data points	Q _g : MScf/Day, P _u and P _d : Psig, D ₆₄ : inch, γ _g : -, T: °F	a= 0.0001, b= 2.3481935, c= 1, d= 0.0001, e= 1.0360972, f= 1.498291	0.9677	APD%= 5.32

2019	Nasriani et al. [30]	$Q_g = a * \frac{\Delta p^b * D_{64}^c}{LGR^d}$	234 data points	Q _g : MMScf/Day, Δp: Psi, D ₆₄ : inch, LGR: STB/MMScf	a= 0.0437, b=0.4836, c= 1.1136, d= 0.3129	Best result: 0.97	Best result: AAPD%= 8.71
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Table 2. Implementation of some machine learning algorithms to predict oil, gas, and gas condensate flow rates through wellhead wells.

Fluid Flow Type	Authors / Year	Machine Learning Techniques	Dataset	Input Parameters	R ²	Error Functions
Oil flow rate	Payaman & Salavati (2012) [54]	Artificial Neural Network (ANN)	196 data points	P _u - D ₆₄ - GOR	0.98	APD%= -0.33
	Nejatian et, al (2014) [55]	Least-Squares Support Vector Machine (LSSVM)	171 data point	Reynolds number - d/D - Choke flow coefficient	0.99	AAPD%= 0.256
	Gholgheysari Gorjaei et, al. (2015) [56]	Particle swarm optimization (PSO)-Least square support vector machine (LSSVM -PSO)	276 data points	P _u - D ₆₄ - GLR	0.965	APD%= -0.80

	Rostami & Ebadi (2017) [57]	Gene expression programming (GEP)	119 data points	$P_u - D_{64} - GOR - \gamma_g - API$	0.96	AAPD%= 14.808
	Ghorbani et, al. (2019) [50]	Genetic Algorithm and solver optimizers	127 data points	$P_u - D_{64} - GLR - BS\&W\%$	0.99	AAPD%=7.33
	Ghorbani et, al. (2020) [49]	Adaptive Neuro Fuzzy Inference System (ANFIS)	182 data points	$P_u - D_{64} - GLR - BS\&W\%$	0.998	AAPD%= 6.62
Oil flow rate assisted with gas lift	Khan et al. (2020) [51]	ANN	1950 data points	$P_u - D_{64} - T_{up} - P_d - Oil\ API$	0.99	AAPD%= 2.56
Gas flow rate in gas & gas condensate reservoir	ZareNezhad & Aminian (2011) [58]	ANN	97 data points	$\Delta P - GOR - D_{64}$	0.99	APD%= 0.486
	Elhaj et, al. (2015) [59]	ANN	162 data points	$P_u - D_{64} - P_d - T - \gamma_g$	0.99	AAPD%= 0.828
		Fuzzy Logic (FL)			0.97	AAPD%= 0.681
	Kalam et, al. (2019) [59]	ANN	17097	$P_u - D_{64} - T - Q_g$	0.953	AAPD%= 7.386
		Functional Network (FN)	data		0.91	AAPD%= 12
		ANFIS	points		0.95	AAPD%= 14

2. Methodology

2.1. Work Flow

A systematic methodology involving ten steps (Fig. 1) is developed for constructing and evaluating the four hybrid machine learning algorithms employed for the prediction of gas flow rate through wellhead chokes. The first step in the proposed workflow is data gathering from gas condensate fields. Next, the maximum and minimum values of variables need to be determined. Afterward, the variables are normalized between -1 and +1 (Eq. (2)). Once the data are normalized, the set of data is divided into two subsets, training and testing. Then, the machine learning optimizer's accuracy is determined by statistical indicators such as AAPD%, SD, MSE, RMSE, and R². Results obtained from accuracy evaluation are compared with empirical equations and hybrid machine learning techniques [47].

$$x_i^l = \left(\frac{x_i^l - xmin^l}{xmax^l - xmin^l} \right) * 2 - 1 \quad (2)$$

Where x_i^l is the value of attribute l for data record i ; $xmin^l$ is the minimum value of the attribute l among all the data records in the dataset; and $xmax^l$ is the maximum value of the attribute l among all the data records in the dataset.

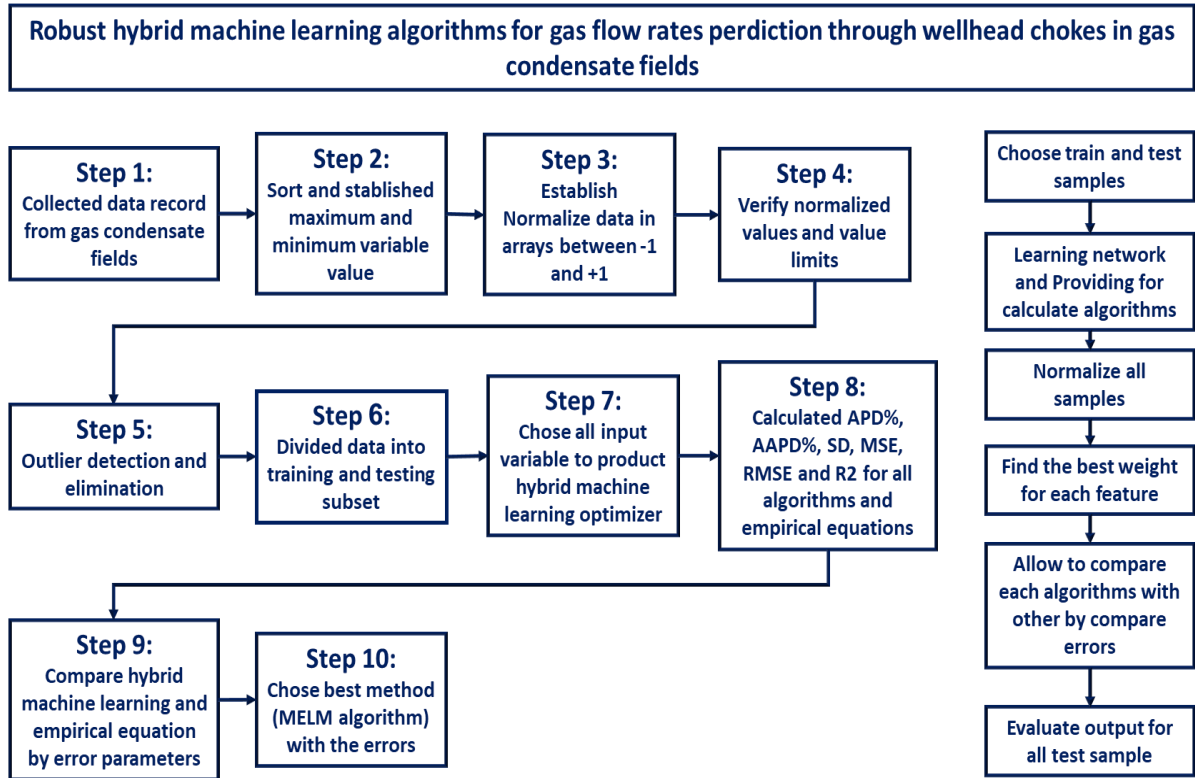


Fig. 1. Schematic of workflow proposed for constrction and evaluation of four HLM algorithms used for Q_g prediction.

2.2. Least square support vector machine (LSSVM)

The least-square support vector machine (LSSVM) is an expanded version of the support vector machine (SVM) that Suykens and Vandewalle developed in 1998 [60, 61]. LSSVM technique uses powerful features of SVM [62, 63]. However, there are two major differences between the LSSVM and SVM learning techniques. First, the LSSVM technique uses square errors in the cost function instead of nonnegative errors, and second, the LSSVM technique applies equality constraints instead of inequality constraints. Consequently, in LSSVM, a linear system of equations is solved instead of a quadratic programming problem, leading to a considerable reduction in the learning model's computational time [64, 65].

In the LSSVM method, the following nonlinear cost function (Eq. (3)) is used for approximation [66, 67]:

$$f(x) = w^T \phi(x_i) + b \quad (3)$$

In which x_i denotes the input variable to the function, the dimension of which is $N \times n$, where N and n stand for the number of samples in the dataset and the number of inputs parameters, respectively. w and b represent the weight and bias vector of output layer respectively, $\phi(x_i)$ indicates kernel function, T is transpose matrix. For the sake of brevity, the readers are advised to refer to the previously published works, where a detailed theoretical description of the LSSVM model is provided [61, 62, 68-73]. Since the LSSVM model parameters have a considerable influence on the model accuracy and performance, GA and PSO optimization algorithms were applied for optimizing those parameters in the present study. Besides these control parameters, the type of kernel applied in LSSVM model construction also has a pronouncing effect on the performance and accuracy of the LSSVM model. Given that there is no standard way in kernel function selection, four of the most commonly applied kernel functions, including the linear kernel, polynomial kernel, radial basis function kernel, and multilayer perceptron kernel, have been tested out in the present study. Among those, the RBF kernel is found to be the most efficient one.

2.3. Multilayer extreme learning machine (MELM)

The extreme learning machine (ELM), as a new quick single hidden layer feedforward network, was first developed by Huang et al. in 2005 [74]. Since its emergence, ELM has been widely used in generating solutions to various problems, namely regression, classification, and clustering. The basic structure of ELM resembles a single hidden layer backpropagation (BP) neural network that is composed of three layers which are

input, hidden, and output layers. However, the method used in training ELM is soundly different from that of the conventional network. Indeed, the ELM technique randomly assigns the hidden parameters, the hidden nodes biases, and the input weights to hidden nodes and analytically calculates the output weights. As a result, the time required for optimizing the hidden parameters of the model is significantly decreased by avoiding iterative calculations during model training [75, 76]. Elaboration on structures and the theoretical principles of conventional artificial neural networks and ELM models can be discovered in previous publications [74, 77-79].

Complex variants of ELM with several hidden layers are recommended to solve problems with a nonlinear dataset of high complexity. Therefore, a complex form of ELM that includes multiple hidden layers, called MELM, was developed based on the deep learning (DL) concept [80]. The construction procedure of the MELM learning model is elaborated in recently published works [38, 63].

2.4. Optimization algorithm techniques

2.4.1. Genetic algorithm (GA)

Genetic algorithm is a class of evolutionary algorithms developed based on natural selection and evaluation principles. This method is commonly applied for solving search and optimization problems. This method obtains the global optimum solution within a complex multi-dimensional space. In the GA method, the poorer population of parents is replaced with the better offspring population by each generation of the population using three operations: selection, crossover, and mutation. This process is reaping by the GA until a high accuracy of prediction is achieved. Hence, the population's final output individual is the best parameter group [81, 82]. Fig. 2 illustrates the cycle of GA. To keep the study concise, the readers are advised to read

previously published studies in which detailed theoretical descriptions on the GA technique are provided [83-86].

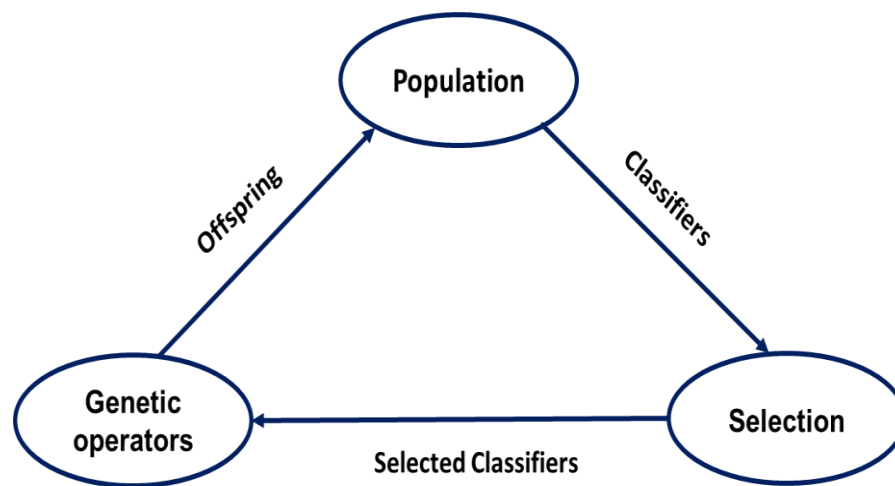


Fig. 2. Schematic of GA cycle.

2.4.2. Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO), an optimization algorithm inspired by natural swarming and flocking of birds and insects, was proposed by Kennedy and Eberhart [87]. This optimization method initiates a population or “swarm” made of random solutions and, by updating generation, attempts to obtain the optimal solution. In the PSO algorithm, solutions are named “particles” [38]. The population particles go through the space of the problem by following the current best particles in the population. Each of the population particles possesses a velocity and a position, and they seek positions with good fitness in the space. During the optimization process, two main pieces of information are memorized by each particle i) the best position heaving been so far visited by the particle (Pb) ii) the global best position attained by the particles in the whole swarm (Gb) [29, 38]. To obtain the best solution, several iterations are performed by PSO. In each step, the solution achieved is compared with

both the global best and the self-local best of the population. The new position of particles can be obtained by Eqs. (4) and (5).

$$V_i(t+1) = wV_i(t) + c_1r_1(Pb_i(t) - x_i(t)) + c_2r_2(G_b(t) - x_i(t)) \quad (4)$$

$$x_i(t+1) = x_i(t) + V_i(t+1), \quad i = 1, 2, \dots, N \quad (5)$$

Where N indicates the number of swarm particles, x_i and V_i represent the position and velocity of the particles respectively, w stands for inertia weight, controlling the influence of the previous velocity on the new one, c_1 and c_2 denote the cognitive and social acceleration coefficient, respectively, and r_1 and r_2 are two random numbers ranging from 0 to 1. It should be noted that, w , c_1 , and c_2 can be obtained through performing a trial and error analysis on the dataset under evaluation [88, 89].

2.5. Hybrid machine-learning models developed for Q_g prediction

In this study, four hybrid machine-learning models equipped with effective optimizers are proposed, which provide accurate and reliable predictions of gas flow rate through wellhead chokes. LSSVM and MELM learning algorithms are coupled with two optimization algorithms (GA and PSO) to develop these predictive models.

2.5.1. LSSVM-PSO/GA hybrid models

In this study, two hybrid models LSSVM-PSO and LSSVM-GA, are developed for predicting gas flow rate through the chocks. Fig. 3 displays the flow diagram for the LSSVM- PSO/GA models developed.

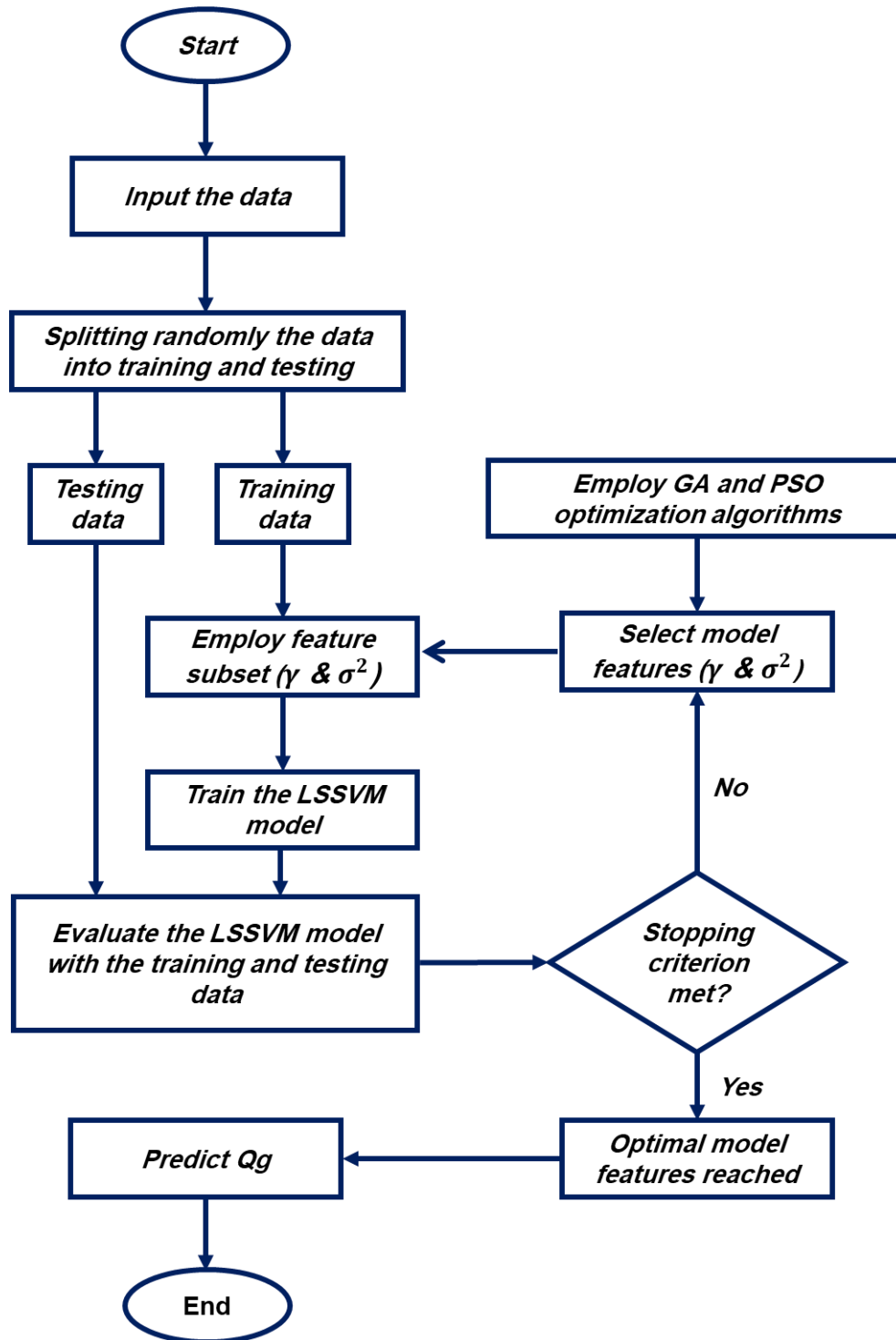


Fig. 3. Typical flow diagram for LSSVR-PSO/GA hybrid models developed for Q_g prediction.

The optimal values of the LSSVM model hyperparameters were obtained using PSO and GA optimization algorithms. RBF kernel function was employed in the LSSVM

predictive model construction since it provides the best performance among all the kernel functions tested (table 1). The LSSVM hyperparameters for the hybrid models developed, LLSVM-GA and LSSVM-PSO, and the control parameters for the GA and PSO optimization algorithms applied are listed in Table 3.

Table 3. Optimal values of control parameters for the LSSVM-PSO/GA models established for Q_g prediction.

LSSVM		PSO		GA	
Control parameter	Value	Control parameter	Value	Control parameter	Value
Variance of RBF kernel σ^2	9.8507	Swarm size	80	Population	80
Regularization parameter	53.1392	Maximum iterations	200	Maximum iterations	200
Objective function		Social constant	2.05	Selection method	Roulette wheel
		cognitive constant	2.05	crossover	uniform(p=1)
		Inertia weight	0.98	mutation	uniform(p=1)
				mutation rate	0.08
				selection pressure	2

				(Roulette wheel)	
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311

312 **2.5.2. MELM-PSO/GA hybrid models**

313 Coupling MELM algorithm with GA and PSO optimization, two other hybrid models,
314 MELM-PSO and MELM-GA, were constructed for accurately and reliably predicting
315 gas flow rate through wellhead chokes. The genetic algorithm is inherently discrete,
316 while the PSO algorithm is a continuous method. Both of these algorithms generate
317 new responses in the neighborhood of the two parents (in the genetic algorithm with
318 the crossover operator and the PSO by adsorption to the best position in the P_{best}
319 particle community). Generating answers in the neighborhood of two parents can be
320 one of the most obvious differences with point-based methods such as simulated
321 annealing and taboo search. Execution time in GA is longer than in PSO, and it
322 converges more slowly. The PSO, on the other hand, converges faster due to fewer
323 operators and fewer parameters. More details on the GA and PSO algorithms can be
324 found in previous publications [90-93]. A flow diagram for the MELM-PSO/GA hybrid
325 models developed is illustrated in Fig. 4. As can be seen from Fig. 4, the developed
326 hybrid models include a two-step procedure of optimization, which is briefly described
327 below:

328 Step1: Determining the optimal number of hidden layers using the optimizers applied
329 by a tuning optimization procedure. The ranges of the numbers of hidden layers and
330 the nodes in those layers are narrowing optimally down. The narrow ranges will then
331 be employed as constraints in constructing hybrid models.

Step 2: Calculating the MELM model's control parameters (weights and biases) for the constrained ranges of the hidden layers and the nodes in those layers obtained at step 1.

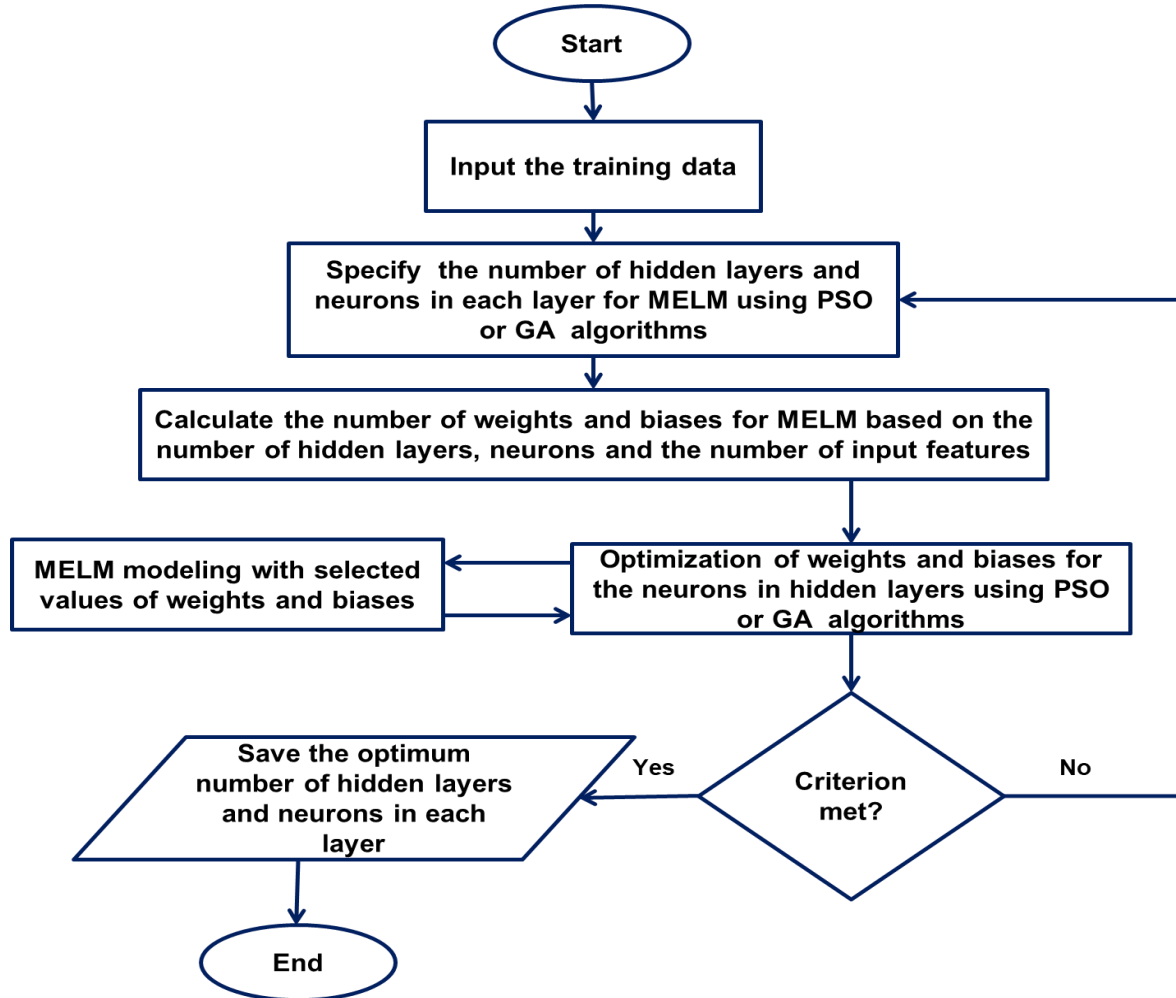


Fig. 4. Typical Flow diagram of MELM-PSO developed for Q_g prediction.

Based on the first step optimization carried out for the MELM construction, the number of hidden layers for MELM is constrained to a range from 5 to 20. The number of nodes in those hidden layers is constrained to a range from 3 to 9. Table 4 lists the results for the first optimization step, and Table 5 shows the best structure for MELM-PSO/GA models. The control parameters for the MELM-PSO/GA hybrid models are presented in Table 6.

Table 4. RMSE obtained for different MELM structures for pre-processing the MELM-PSO/GA models applied for Q_g prediction.

Number of hidden layers	Number of neurons in the layers			
	3	5	7	9
5	6.3296	5.7488	6.0634	6.0985
10	5.8175	5.2953	5.3296	5.3298
15	5.9542	5.0098	5.0108	5.0152
20	5.9533	5.0279	5.0295	5.1841

Table 5. The best structure for pre-processing the MELM-PSO/GA models applied for Q_g prediction.

Layer	Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	RMSE
Neurons	10	9	14	12	12	8	4.9637

Table 6. Optimal values of control parameters for the MELM-PSO/GA hybrid models established for Q_g prediction.

MELM		PSO		GA	
Control parameter	Value	Control parameter	Value	Control parameter	Value
Number of Input variables	6	Swarm size	80	Population	80
Number of hidden layers	20	Maximum iterations	200	Maximum iterations	200
Number of neurons in each layer	5	Social constant	2.05	Selection method	Roulette wheel

	RMSE	cognitive constant	2.05	crossover	unifor m(p=1)
		Inertia weight	0.98	mutation	unifor m(p=1)
		Var minimum		mutation rate	0.08
		Minimum velocity		selection pressure (Roulette wheel)	2
		Minimum velocity			

352

353 3. Data Collection and Distribution

354 In this paper, for predicting Q_g from gas condensate reservoirs through wellhead
355 chokes, 1067 datasets were collected from three gas condensate fields Marun-Khami,
356 Aghhajari-Khami, and Ahvaz-Khami that located in southwestern Iran (see Fig. 5).
357 Khami group is a group of geological formations of Zagros, which includes Heath and
358 Surmeh formations from the Jurassic period and Fahlian, Gadvan, and Darian
359 formations from the Cretaceous period. This group has crude oil reserves in some oil
360 fields plus gas and condensate gas in most fields. Khami reservoir rock is deeper than
361 the Asmari and Bangestan reservoir rocks. Ahvaz, Gachsaran, Maroon, Karanj, Bibi
362 Hakimeh, and Aghajari fields are among the fields that have crude hydrocarbon
363 reserves (data used in this study are confidential, and the authors have no permission
364 to share them in public). To predict Q_g , six input variables were used in this study,
365 including temperature (T), the upstream pressure (P_u), downstream pressure (P_d), gas
366 gravity (γ_g), choke diameter (D_{64}), and gas-liquid ratio (GLR). To the authors' best
367 knowledge, these six input variables have never been used simultaneously in
368 previously published studies on this topic. Therefore, the models developed in the

present study can be considered novel approaches in this field. Table 7 shows the statistical characteristics of the data variables used to predict the Q_g for each reference in this paper.

Table 7. Statistical characterization of data variables in Iranian gas condensate fields for Q_g prediction.

Statistical characterization of the data variables in Iranian gas condensate fields for Q_g prediction.								
Field	Variables	Temperature	Upstream Pressure	Downstream Pressure	Gas Specific Gravity	Choke Diameter	Gas Liquid Ratio	Gas Flow Rate
	Symbol	T	Pu	Pd	γ_g	D64	GLR	Q_g
	Units	(F)	(Psig)	(Psig)	-	(Inch)	(Scf/STB)	(Mscf/Day)
297 dataset records from Gas Condensate Field (A)	Mean	125.81	1791.70	759.82	0.68	41.94	8.60E+04	20.08
	Std. Deviation	19.67	755.80	350.69	0.04	22.22	7.64E+04	5.99
	Variance	385.67	5.69E+05	1.23E+05	0.00	492.05	5.82E+09	35.76
	Minimum	74.00	217.00	100.00	0.61	16.00	7.46E+03	5.40
	Maximum	187.00	6115.00	2615.00	0.82	160.00	3.22E+05	29.55
	Skewness	0.0894	-0.1461	-0.0105	1.4158	3.0942	1.29E+00	-0.2408
	Kurtosis	-0.1333	3.0393	1.9411	3.1418	10.9981	1.20E+00	-0.9674
	Median	125.00	2043.00	891.00	0.67	40.00	5.76E+04	20.37
399 dataset records from Gas Condensate Field (B)	Mean	132.18	2045.11	912.01	0.68	128.29	5.98E+04	73.55
	Std. Deviation	22.74	749.42	338.94	0.03	48.86	4.46E+04	17.16
	Variance	515.71	5.60E+05	1.15E+05	0.00	2381.35	1.99E+09	293.70
	Minimum	77.00	1036.00	223.86	0.61	42.00	6.36E+03	54.13
	Maximum	189.00	4658.00	2366.82	0.82	194.00	2.69E+05	122.46
	Skewness	0.0935	1.8326	1.7252	1.3309	-0.1945	1.68E+00	0.8917
	Kurtosis	-0.1346	3.3988	5.0902	3.8104	-1.2896	3.99E+00	-0.2748
	Median	132.00	1880.00	887.00	0.67	130.00	5.36E+04	67.25
371 dataset records from Gas Condensate Field (C)	Mean	129.15	2083.33	896.10	0.67	82.99	7.46E+04	42.58
	Std. Deviation	18.91	607.65	322.13	0.04	43.71	6.05E+04	7.16
	Variance	356.56	3.68E+05	1.03E+05	0.00	1905.69	3.66E+09	51.06
	Minimum	85.00	952.00	125.00	0.61	26.00	7.91E+03	29.57
	Maximum	187.00	5910.00	2265.30	0.82	194.00	3.22E+05	53.99
	Skewness	0.1189	2.2510	0.7916	1.4640	1.0655	1.75E+00	-0.1667
	Kurtosis	-0.0658	10.1780	3.6853	3.0654	-0.0534	3.00E+00	-1.1974
	Median	129.00	2088.74	951.00	0.67	64.00	6.18E+04	43.00
1067 dataset records from Gas Condensate Fields (A, B and C)	Mean	129.35	1987.86	864.12	0.68	88.50	7.23E+04	47.90
	Std. Deviation	20.76	715.25	342.50	0.04	53.84	6.12E+04	24.68
	Variance	430.67	5.11E+05	1.17E+05	0.00	2896.15	3.75E+09	608.75
	Minimum	74.00	217.00	100.00	0.61	16.00	6.36E+03	5.40
	Maximum	189.00	6115.00	2615.00	0.82	194.00	3.22E+05	122.46
	Skewness	0.1442	1.1531	0.8138	1.3982	0.6632	1.73E+00	0.6162
	Kurtosis	-0.0303	5.0324	3.8315	3.2852	-0.9592	3.21E+00	-0.0940
	Median	129.00	1990.00	908.00	0.67	64.00	5.57E+04	46.84
	Mode	114.00	1986.00	611.50	0.67	64.00	8.14E+04	67.41

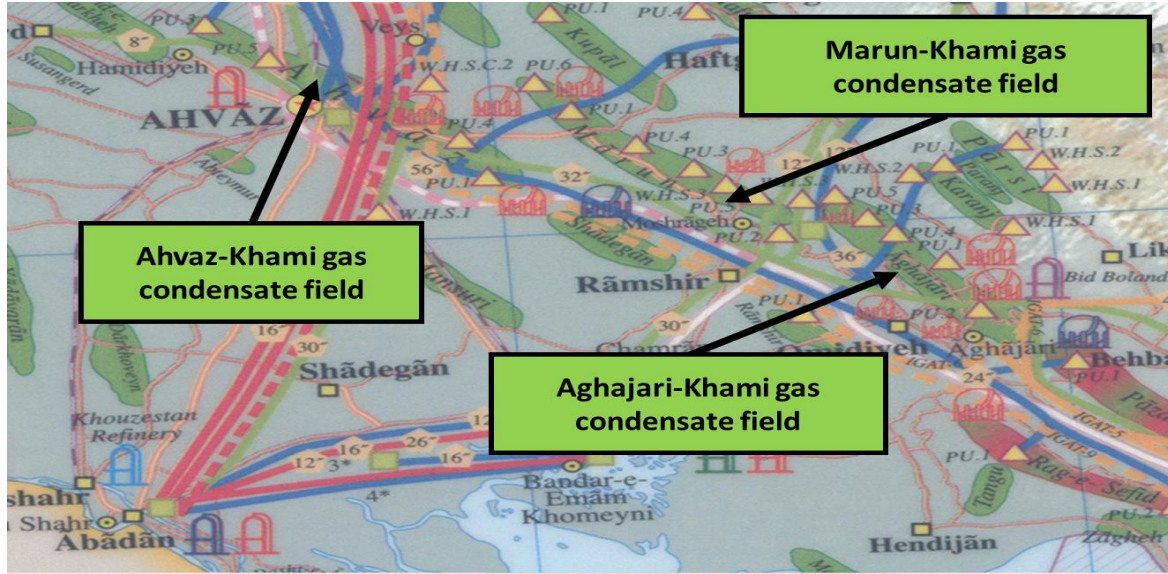


Fig. 5. Marun-Khami, Aghajari-Khami, and Ahvaz-Khami gas condensate fields located onshore Iran in the Zagros Basin.

One of the descriptive diagrams to describe the input data is cumulative distribution functions (CDF) shown in Fig. 6. In this figure (Fig. 6), the 1067 dataset distribution diagram is used, and the CFD formula is shown in Eq. (6) [47, 49]:

$$F_X(x) = P(X \leq x), \text{ for all } x \in R \quad (6)$$

X is the data variable value range, x is the value of variable x in a specific data record, and R is the dataset of data records.

CFD is used to describe the input variables in Fig. 6. The CFD for temperature is $T < 112 \text{ F}^0$ for ~ 20.3% of the data records, $112 < T < 152 \text{ F}^0$ for ~ 64.7% of the data records, and $T > 152 \text{ F}^0$ for the remaining 15% of the data. The CFD for initial gas specific gravity is $\gamma_g < 0.6588$ for ~ 29.8% of the data records, $0.6588 < \gamma_g < 0.7188$ for ~ 64.4% of the data records, and $\gamma_g > 0.7188$ for the remaining 5.8% of the data. The CFD for gas to liquid ratio is $\text{GLR} < 22243 \text{ Scf/STB}$ for ~ 21.2% of the data records, $22243 < \text{GLR} < 140000 \text{ Scf/STB}$ for ~ 60% of the data records, and $\text{GLR} > 140000 \text{ Scf/STB}$ for the remaining 18.8% of the data. The CFD for gas flow rate is $Q_g < 18.3$

394 Mscf/Day for ~ 11.3% of the data records, $18.3 < Q_g < 72.8$ Mscf/Day for ~ 76.3% of
395 the data records, and $Q_g > 72.8$ Mscf/Day for the remaining 12.4% of the data. Based
396 on the CFD's shown in Fig. 6, three variable parameters, including T , γ_g , and GLR are
397 normally distributed.

398 The CFD for upstream pressure is $P_u < 2080$ psig for ~ 56.4% of the data records,
399 $2080 < P_u < 3220$ psig for ~ 39% of the data records, and $P_u > 3220$ psig remaining
400 4.6% of the data. The CFD for downstream pressure is $P_d < 498.1$ psig for ~ 13.67%
401 of the data records, $498.1 < P_d < 966$ psig for ~ 48.43% of the data records, $966 < P_d$
402 < 1421 psig for ~ 35% of the data records, and $P_d > 1421$ psig for the remaining 2.9%
403 of the data. The CFD for choke size is $D_{64} < 40$ inch for ~ 20% of the data records, 40
404 $< D_{64} < 108$ inch for ~ 46% of the data records, and $D_{64} > 108$ inch for the remaining
405 34% of the data. Based on the CFDs shown in Fig. 6, three variable parameters,
406 including P_u , P_d , and D_{64} , are not normally distributed.

407

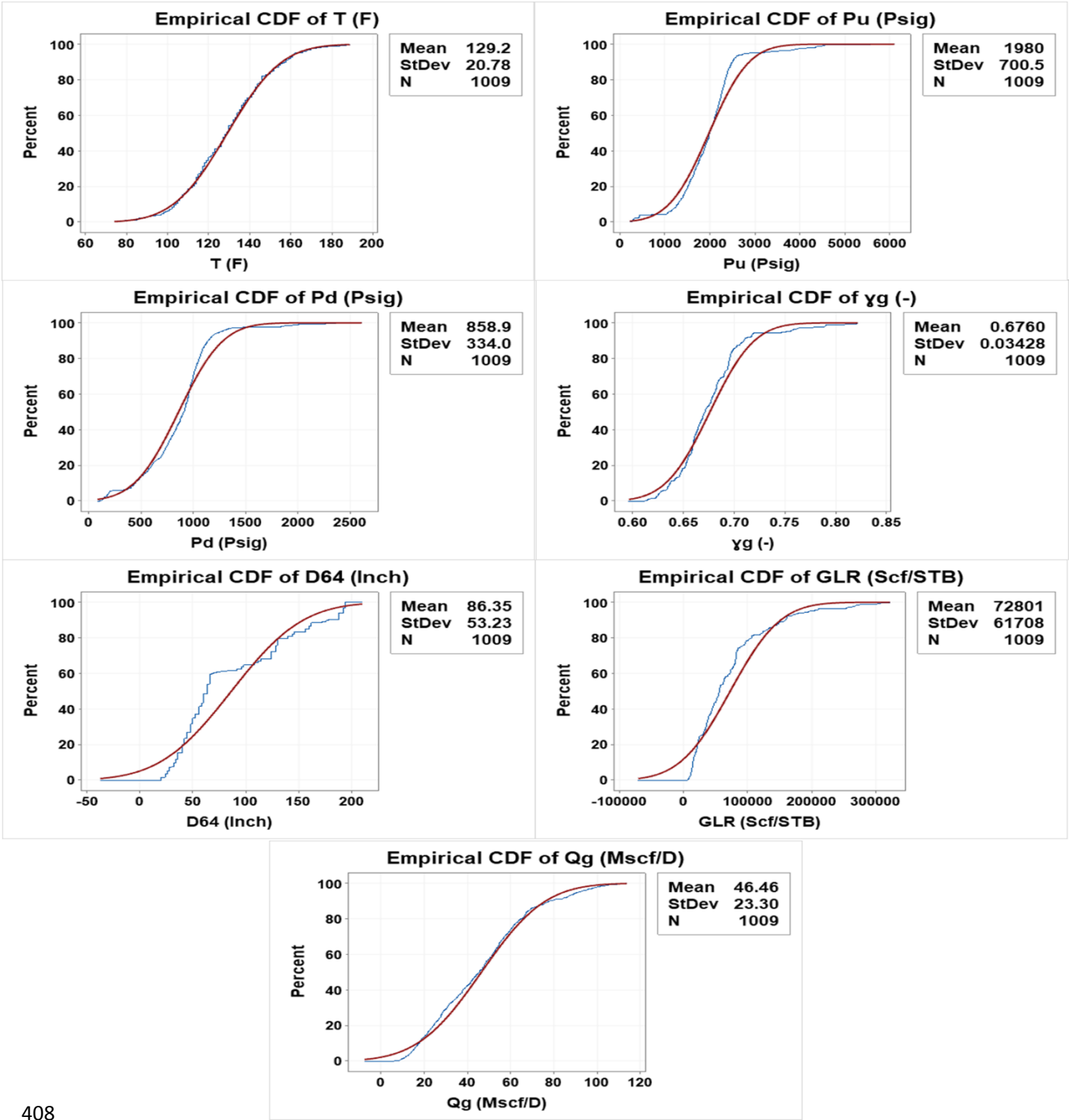


Fig. 6. Cumulative distribution function (CDF) for the input variables and output values used for the Q_g prediction (thinner blue line) compared to cumulative

distribution functions for normal distributions defined by variable means and standard deviations (thicker red line).

4. Results & Discussion

Fig. 7 presents the relationship between the input variables (T , P_u , P_d , D_{64} , γ_g , and GLR) and Q_g for information on 1009 data records collected around Iran. Comparison of the input variables correlation with Q_g indicates that D_{64} presents a strong correlation with Q_g , which suggests this parameter is more influential on Q_g than other parameters. Besides, the least influential parameter on the output variable (Q_g) is found to be γ_g . This evaluation of the inputs parameters' correlation degree with Q_g can assist in the proper selection of features for the algorithms, leading to enhanced prediction performance and accuracy.

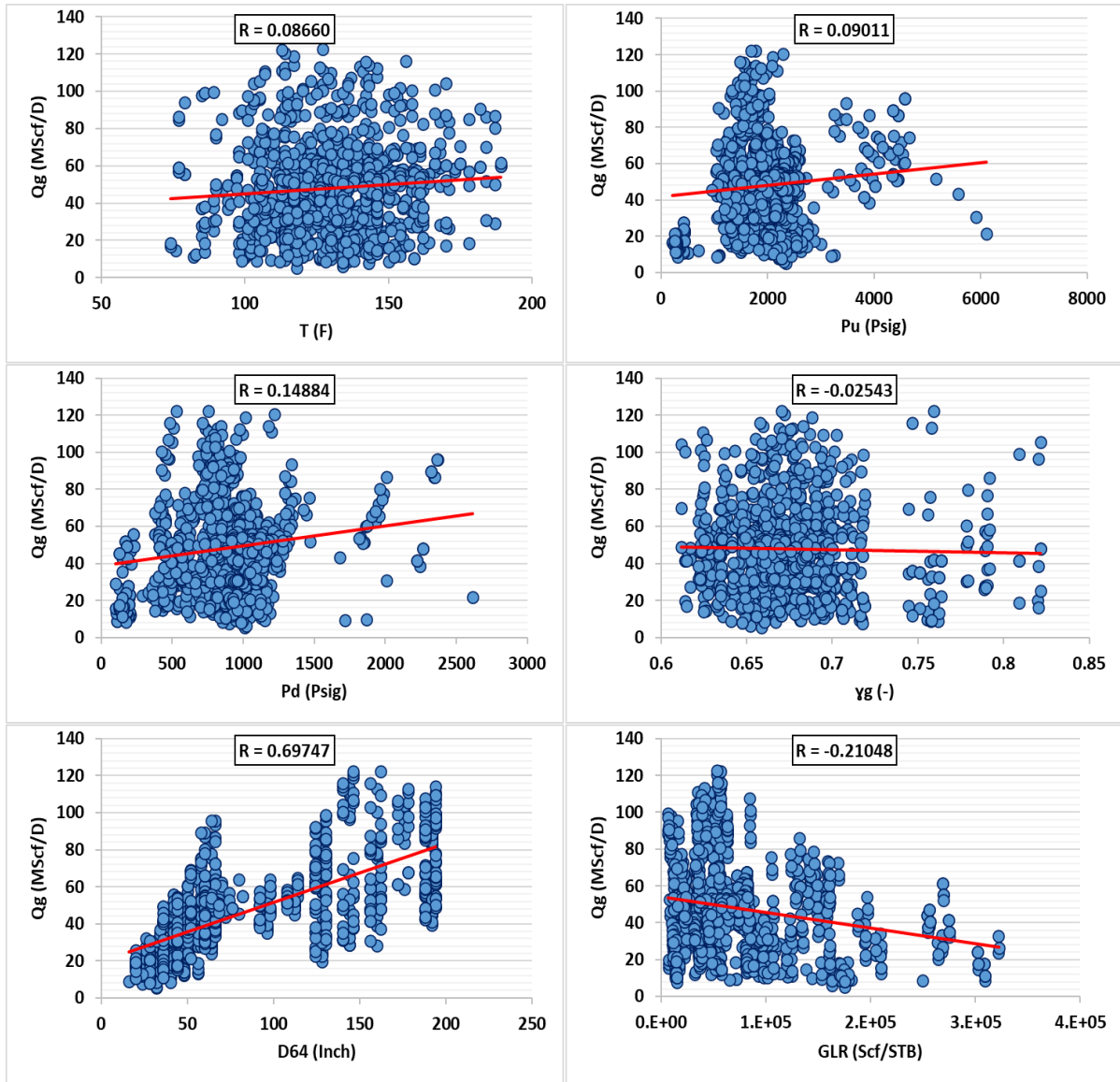


Fig. 7. Cross plot of input variables versus Q_g , indicating the effect of boundaries on the performance of four ML models developed.

One way to compare HML and empirical equations' efficiency in Q_g prediction is to use statistical errors. For this purpose, the equations determining the magnitude of error, including percentage deviation (PD) or relative error (RE), average percentage deviation (APD), absolute average percentage deviation (AAPD), standard deviation (SD), mean square error (MSE), root mean square error (RMSE; the objective function

of the HML models), and coefficient of determination (R^2) are selected for prediction accuracy evaluation, which are given in Eqs. (7) to (13):

Percentage deviation (PD) or relative error (RE):

$$PD_i = \frac{H_{(Measured)} - H_{(Predicted)}}{H_{(Measured)}} \times 100 \quad (7)$$

Average percentage deviation (APD):

$$APD = \frac{\sum_{i=1}^n PD_i}{n} \quad (8)$$

Absolute average percentage deviation (AAPD):

$$AAPD = \frac{\sum_{i=1}^n |PD_i|}{n} \quad (9)$$

Standard Deviation (SD):

$$SD = \sqrt{\frac{\sum_{i=1}^n (D_i - D_{mean})^2}{n-1}} \quad (10)$$

$$D_{mean} = \frac{1}{n} \sum_{i=1}^n (H_{Measured_i} - H_{Predicted_i})$$

Mean Square Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (Z_{Measured_i} - Z_{Predicted_i})^2 \quad (11)$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{MSE} \quad (12)$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^N (H_{Predicted_i} - H_{Measured_i})^2}{\sum_{i=1}^N (H_{Predicted_i} - \frac{\sum_{i=1}^N H_{Measured_i}}{n})^2} \quad (13)$$

These statistical indicators are among the most commonly used indicators to evaluate the prediction performance accuracy and compare HML algorithms and empirical

equations. Among these indicators, RMSE is considered the most important one for evaluating HLM models' prediction accuracy. Given these algorithms are configured to minimize the RMSE, this accuracy indicator is more important than other statistical errors studied in this research.

Using statistical errors, the data are divided into two parts: test and train. Tables 8 to 10 show a comparison between the performance accuracy of HML algorithms and empirical models for (712 data records training: 70%), testing (297 data records: 30%), and total subset (1009 data records: 100%) of Iran condensate field data, respectively.

Table 8. Gas flow rate Prediction accuracy statistics for the training subset (712 available data records; ~70%) Marun-Khami, Aghajari-Khami, and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).

Gas flow rate Prediction accuracy statistics for the training subset (712 available data records; ~70%) Marun-Khami, Aghajari-Khami and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).						
Models	APD	AAPD	SD	MSE	RMSE	R2
Units	(%)	(%)	(Mscf/Day)	(Mscf/Day)	(Mscf/Day)	-
Empirical equations						
Osman & Dokla	-93.977	97.968	54.156	5004.2328	70.7406	0.4017
Al-Attar	74.364	83.219	59.382	3991.2958	63.1767	0.4271
Seidi & Sayahi	52.487	61.372	25.974	982.3102	31.3418	0.4952
Ghorbani et al.	31.663	47.116	19.167	602.5881	24.5477	0.4954
Nasriani et al.	47.380	77.087	47.066	2228.3030	47.2049	0.4862
Hybrid machine learning optimizer algorithms						
MELM-PSO	-2.237	5.471	2.592	6.7242	2.5931	0.9900
MELM-GA	-3.179	6.459	3.048	9.3848	3.0635	0.9862
LSSVM-PSO	-5.115	10.870	4.734	22.4867	4.7420	0.9655
LSSVM-GA	-5.194	10.961	5.025	25.3992	5.0398	0.9595

Table 9. Gas flow rate Prediction accuracy statistics for the testing subset (297 available data records; ~30%) Marun-Khami, Aghajari-Khami, and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).

Gas flow rate Prediction accuracy statistics for the testing subset (297 available data records; ~30%) Marun-Khami, Aghajari-Khami and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).						
Models	APD	AAPD	SD	MSE	RMSE	R2
Units	(%)	(%)	(Mscf/Day)	(Mscf/Day)	(Mscf/Day)	-
Empirical equations						
Osman & Dokla	-79.112	85.145	47.094	3570.9979	59.7578	0.4392
Al-Attar	69.478	78.021	56.247	3484.8769	59.0328	0.4495
Seidi & Sayahi	55.115	62.059	21.376	924.7682	30.4100	0.4604
Ghorbani et al.	31.160	44.767	18.457	555.9255	23.5781	0.4895
Nasriani et al.	49.449	78.246	46.719	2182.6987	46.7194	0.4651
Hybrid machine learning optimizer algorithms						
MELM-PSO	-3.150	7.220	3.426	11.7437	3.4269	0.9833
MELM-GA	-6.576	12.638	5.840	34.2741	5.8544	0.9508
LSSVM-PSO	-8.134	16.594	6.939	48.2444	6.9458	0.9269
LSSVM-GA	-7.777	15.653	7.051	49.8530	7.0607	0.9241

Table 10. Gas flow rate Prediction accuracy statistics for the total subset (1009 available data records; ~100%) Marun-Khami, Aghajari-Khami, and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).

Gas flow rate Prediction accuracy statistics for the total subset (1009 available data records; ~100%) Marun-Khami, Aghajari-Khami and Ahvaz-Khami gas condensate fields (Q_g ; MScf/Day).						
Models	APD	AAPD	SD	MSE	RMSE	R2
Units	(%)	(%)	(Mscf/Day)	(Mscf/Day)	(Mscf/Day)	-
Empirical equations						
Osman & Dokla	-89.602	94.194	52.391	4582.3589	67.6931	0.4190
Al-Attar	65.448	75.645	53.425	2699.2699	51.9545	0.4239
Seidi & Sayahi	49.657	61.574	24.809	965.3727	31.0704	0.4810
Ghorbani et al.	31.515	46.424	18.964	588.8529	24.2663	0.4905
Nasriani et al.	48.831	77.428	47.004	2214.8793	47.0625	0.4744
Hybrid machine learning optimizer algorithms						
MELM-PSO	-2.506	5.986	2.863	8.2017	2.8639	0.9778
MELM-GA	-4.179	8.278	4.074	16.7110	4.0879	0.9693
LSSVM-PSO	-6.004	12.555	5.476	30.0685	5.4835	0.9534
LSSVM-GA	-5.955	12.342	5.697	32.5972	5.7094	0.9484

Having a close look at the results presented in Tables 8 to 10 reveals that the prediction accuracy of the MELM-PSO algorithm, which is a novel algorithm, is higher than other HML algorithms and empirical equations. For instance, the MELM-PSO model has: RMSE = 2.5931 MScf/Day; AAPD = 5.471%; $R^2 = 0.9900$ (for training subset); RMSE = 3.4269 MScf/Day; AAPD = 7.220%; $R^2 = 0.9833$ (for testing subset); and RMSE = 2.8639 MScf/Day; AAPD = 5.986%; $R^2 = 0.9778$ (for total subset). Besides, HML models are found to be much more efficient than empirical models in terms of prediction accuracy. Comparing the HLM models' prediction performance suggests that comparable prediction accuracy is reached by all four models. Still, the prediction accuracy reached by the MELM-PSO model is slightly higher than those of the MELM-GA and the LSSVM-PSO/GA models.

Fig. 8 shows the Measured versus predicted gas flow rate (Q_g) for each data record in the training, testing, and total subset evaluated for the Iranian condensate fields. Based on the performance accuracy shown in Fig. 8, it is clear that the performance accuracy of HML algorithms is close to each other. In other words, the results of the LSSVM algorithm hybridized with GA / PSO are very close to MELM hybridized with GA / PSO. As shown in Fig. 8, the coefficient of determination value for the MELM-PSO algorithm is much better than other hybrid algorithms. Comparison of the results presented in Tables 8 to 10 and Fig. 8 suggests that the MELM-PSO can achieve higher performance accuracy compared to other models developed in this study. Based on the accuracy, algorithms can be sorted as MELM-PSO > MELM-GA > LSSVM-PSO > LSSVM-GA.

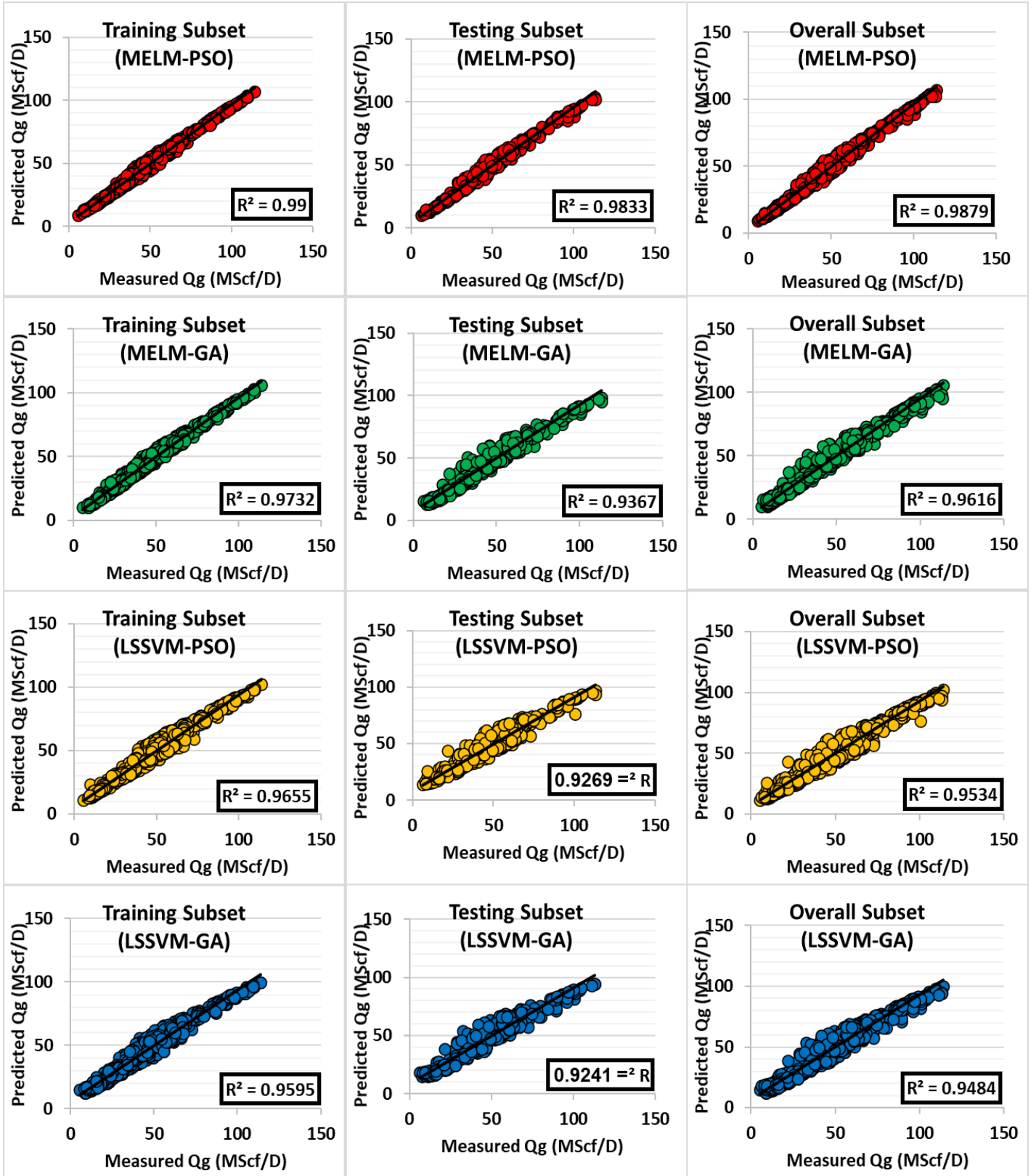


Fig. 8. Measured versus predicted gas flow rate (Q_g) for each data record in the training, testing, and total subset evaluated for HML algorithms (MELM-PSO/GA

and LSSVM-PSO/GA) from the Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami).

Comparison of the results displayed in Figs. 8 and 9 demonstrate that the prediction accuracy of the four HML models developed is much higher than those of previous empirical equations. Based on the prediction accuracy (RMSE), they are as follows: MELM-PSO > MELM-GA > LSSVM-PSO > LSSVM-GA > Ghorbani et al. > Seidi & Sayahi > Nasriani et al. > Al-Attar > Osman & Dokla.

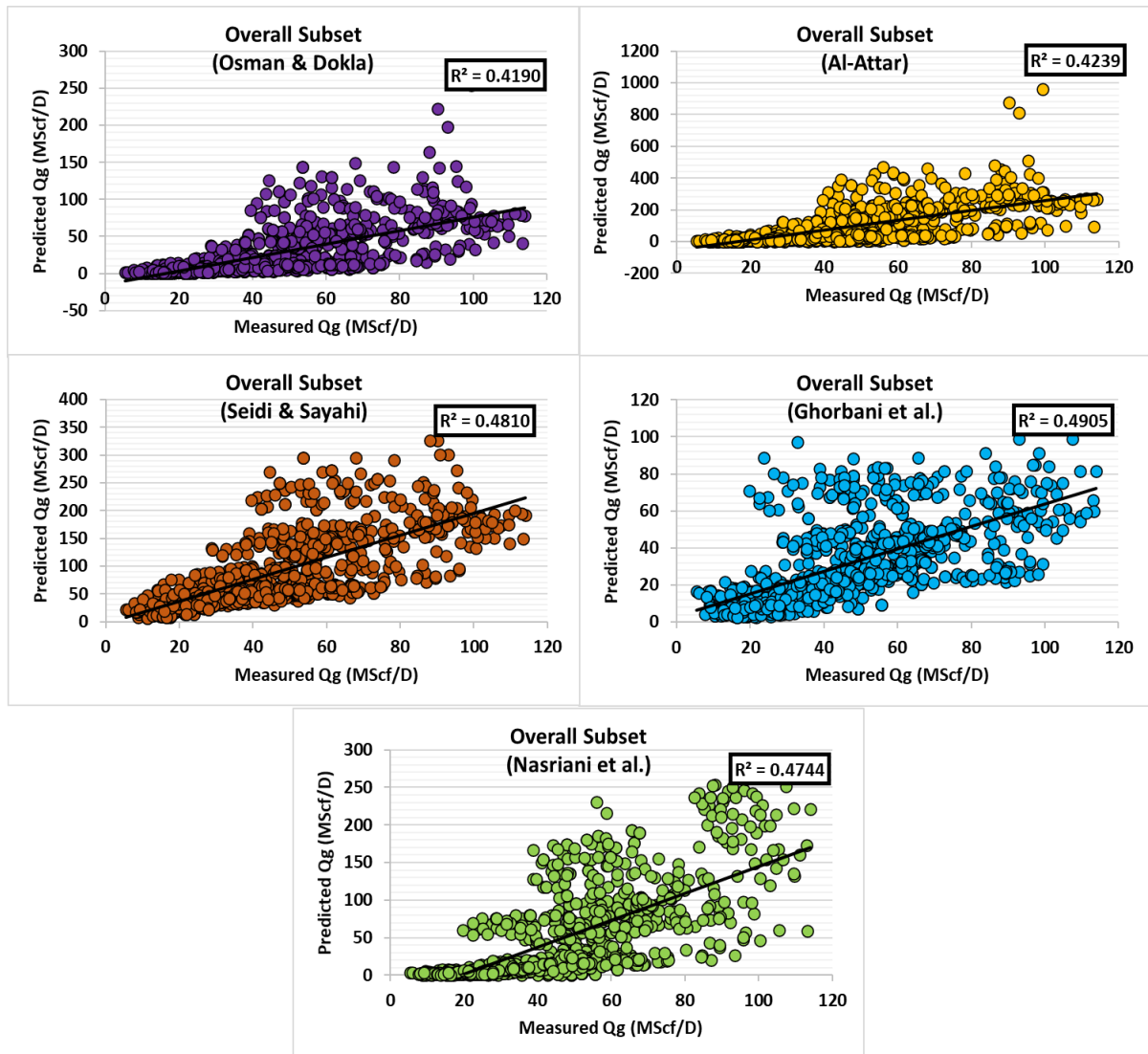


Fig. 9. Measured versus predicted gas flow rate (Q_g) for each data record in the training, testing, and total subset evaluated for empirical equations (Osman & Dokla, Al-Attar, Seeidi & Sayahi, Ghorbani et al., and Nasriani et al.) from the Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami).

Figs. 10 and 11 display the histograms of gas flow rate prediction error with normal distributions (red line) for the HML algorithms and the empirical equations based on 1009 subset data records from the Iranian condensate fields. As shown in Fig. 10, the error rate for the HML is close to zero, and the lowest error for these models is obtained by MELM-PSO. However, the error for all empirical equations is shifted to the right (Fig. 11). According to the results of this figure (Fig. 11), it is clear that the error distribution for the experimental models Osman & Dokla and Al-Attar is asymmetric. All the empirical models involve some individual predictions involving quite large errors, particularly in the positive direction (i.e., overestimates of Q_g). The lowest Q_g prediction error range is associated with is MELM-PSO model.

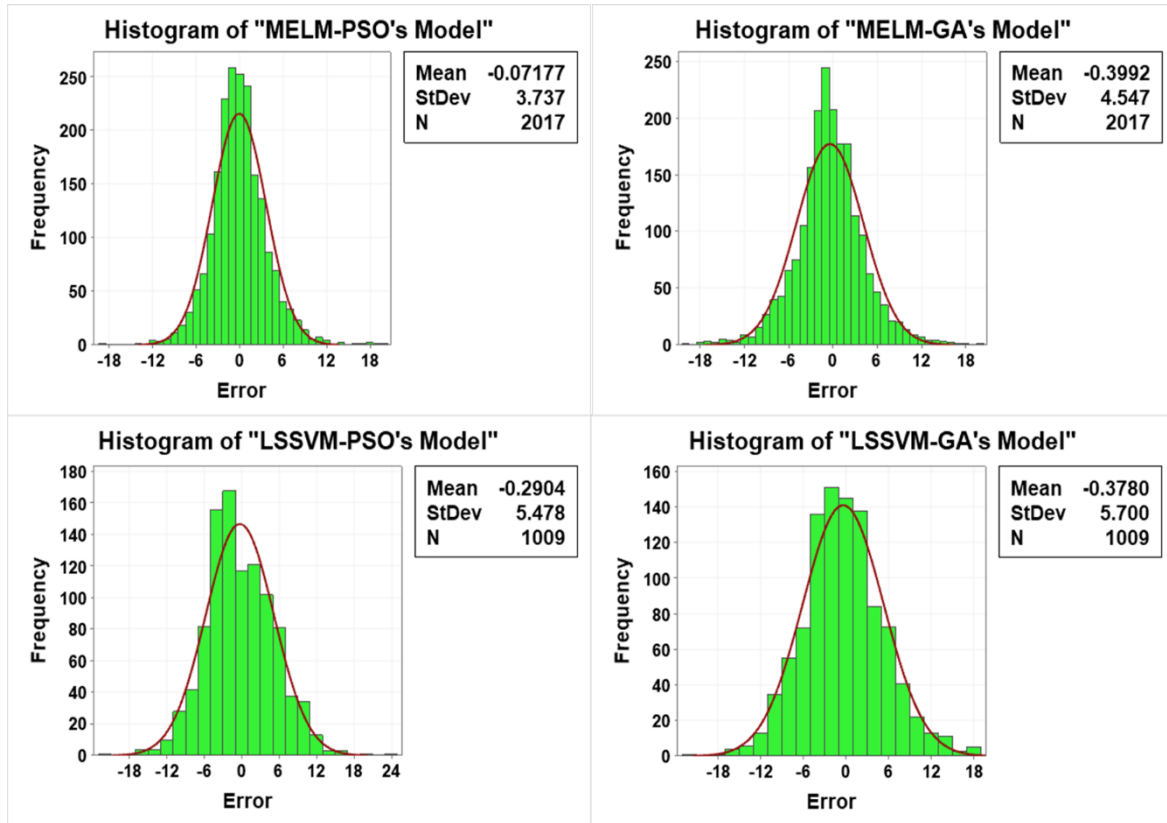


Fig. 10. Gas flow rate prediction error (Q_g) histograms displayed with normal distributions (red line) for HML algorithms based on 1009 subset data records from the Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami).

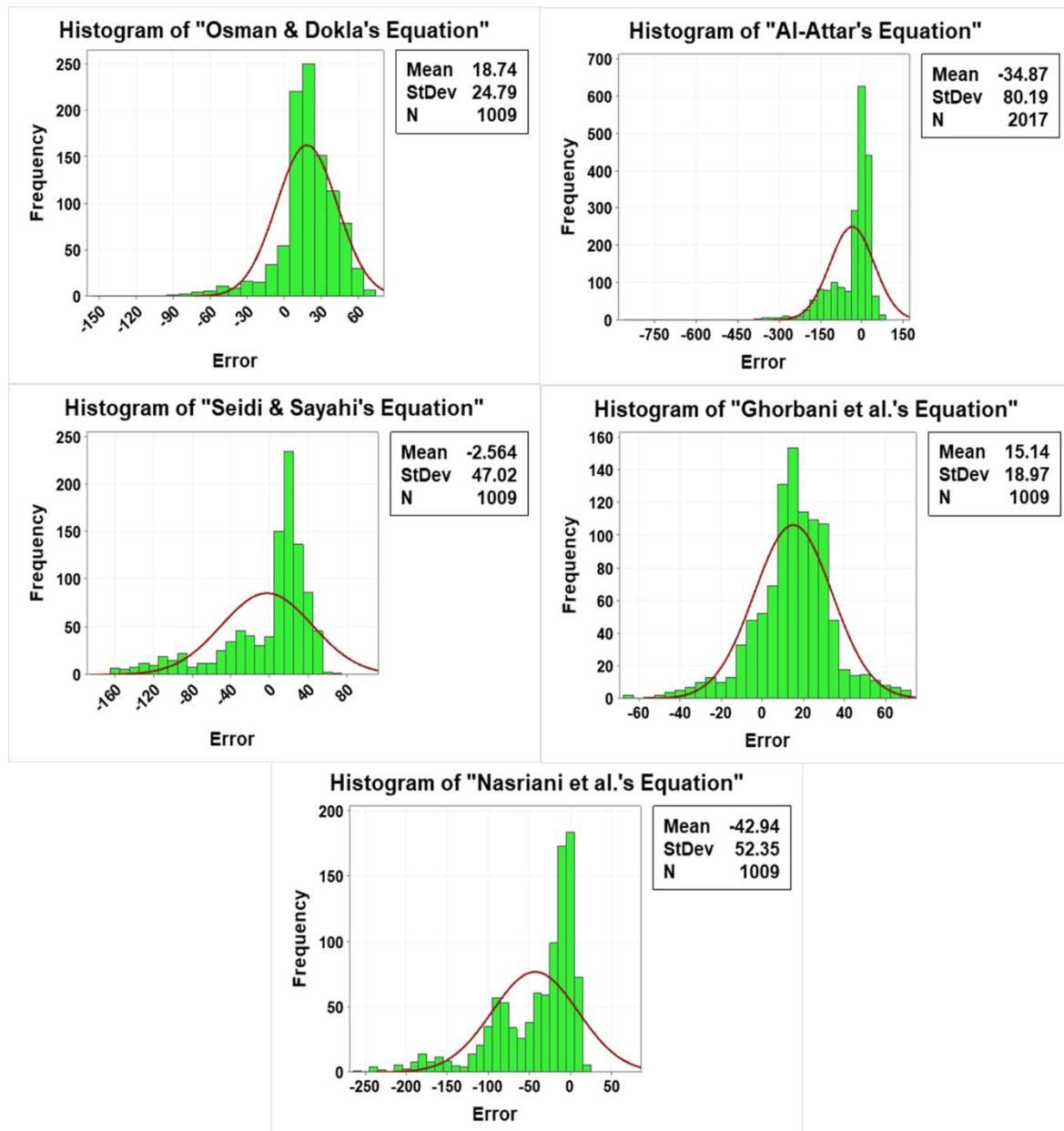


Fig. 11. Gas flow rate prediction error (Q_g) histograms displayed with normal distributions (red line) for empirical equations based on 1009 subset data records from the Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami).

One of the most important and influential factors on the performance accuracy of a prediction model is the use of high-quality data [94, 95]. However, due to the lack of calibration of measuring devices, field data always presents a degree of errors [38]. In

526 other words, there can be data recodes among datasets that are far from the truth.
527 These poor-quality data cause problems in the machine learning process and the
528 training model built on artificial intelligence.

529 When dealing with such data, identifying and deleting unreliable data with distinct
530 outlying values is the best way to increase the model's accuracy. To identify and
531 remove erroneous data parenting in the dataset under study, K-means clustering
532 method in a multidimensional space is used. For this purpose, two to five clusters are
533 considered, which are then divided into smaller clusters [96]. Remote data sets are
534 used as part of the data processing phase to input data into a single-layer ANN
535 network with five neurons to predict Q_g .

536 The results of the K-means clustering performed are shown in Fig. 12. As it can be
537 seen, 3 clusters demonstrate the lowest RMSE for Q_g prediction. Based on this
538 modeling, 58 data sets are identified as outlier data sets. The K-means clustering
539 algorithm can retrieve remote data to predict Q_g . Fig. 13 displays that the k-means
540 clustering presents a promising efficiency in outlier detection for the prediction of Q_g .

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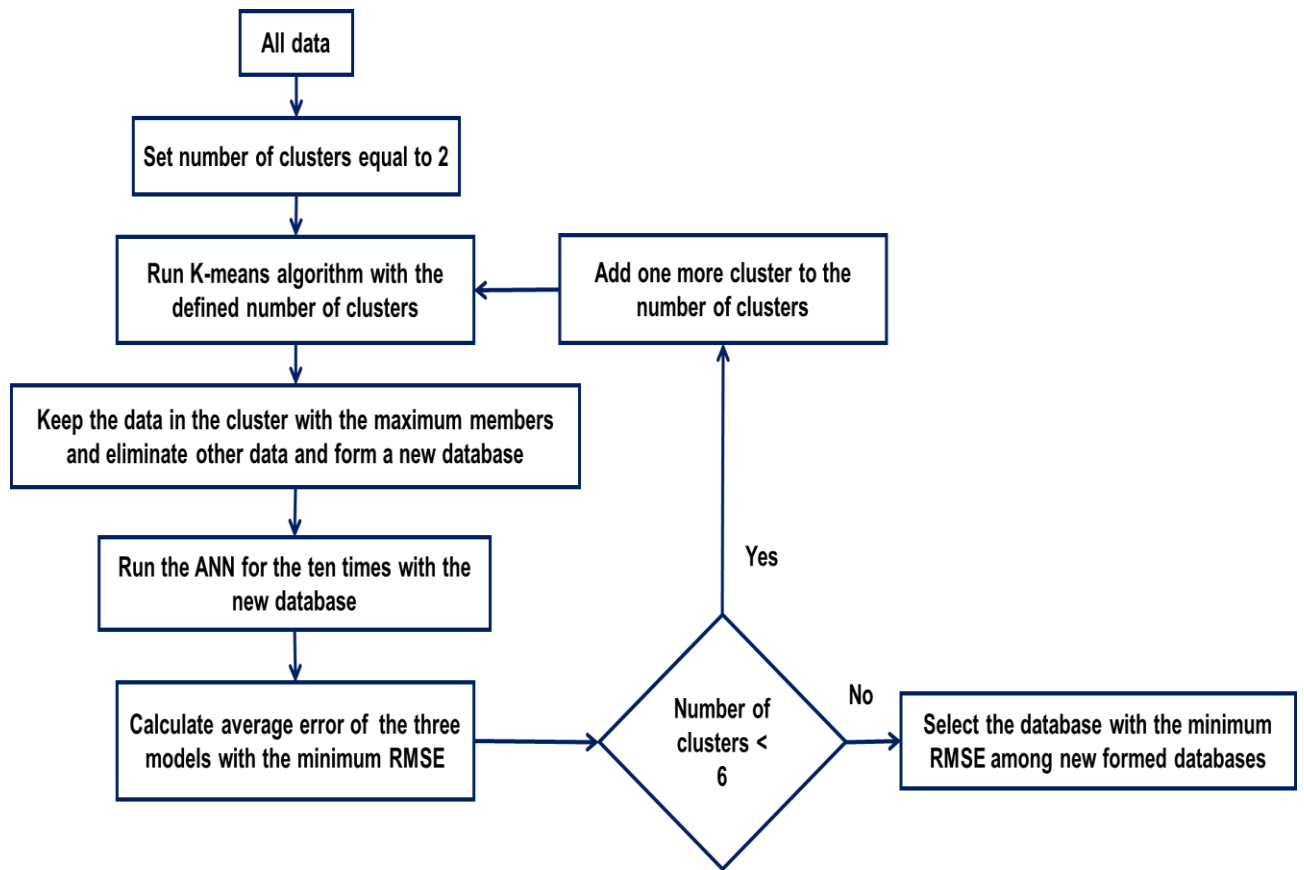


Fig. 12. Schematic of identifying and deleting to data outlier detection using the K-means clustering algorithm [38].

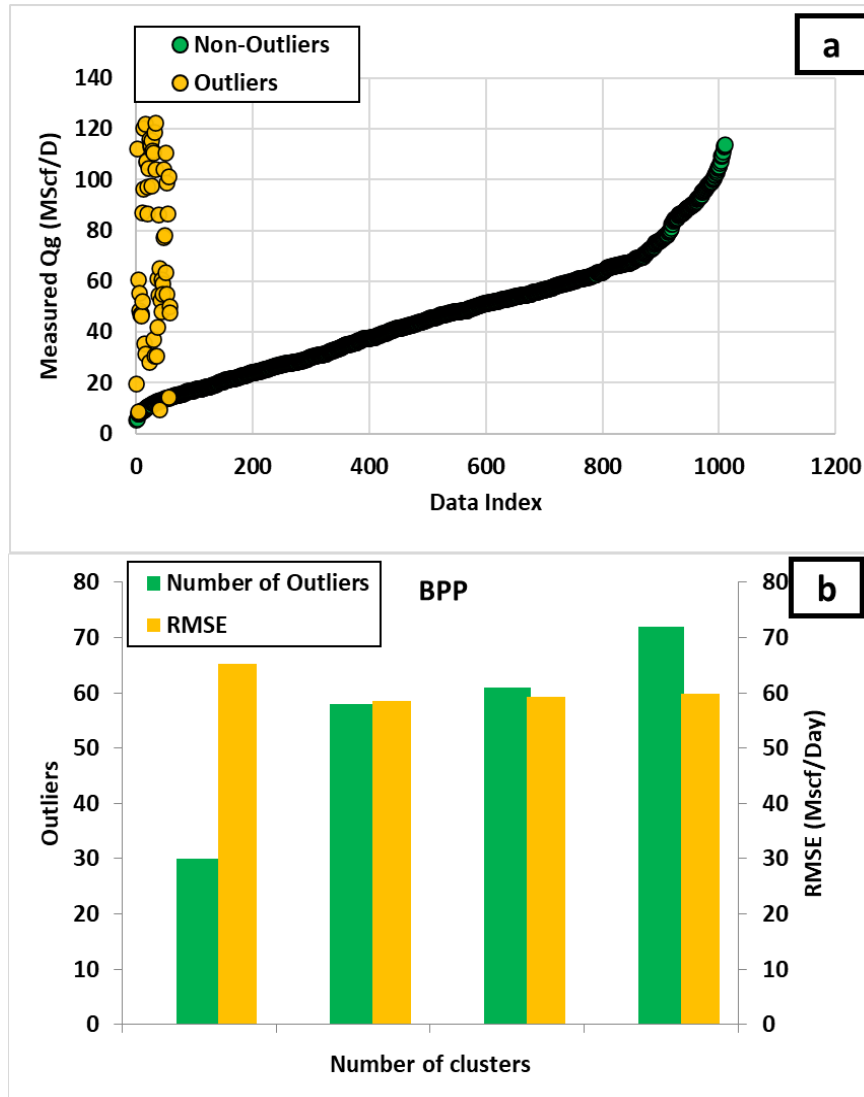


Fig. 13. Results of outlier detection by the K-means clustering algorithm a) Status of remote data detected for Q_g prediction and b) Number of outlying data detected per number of different clusters and ANN modeling error after removal of remote data to predict Q_g .

Fig. 14 demonstrates how the HML models developed progress towards optimal and accurate prediction of Q_g through two hundred iterations. Comparing the results displayed in Fig. 14 indicates that all four HLM algorithms present relatively similar convergence velocity in iteration #3. As seen in iteration #86, the prediction accuracy of LSSVM-PSO is better than that of LSSVM-GA. As for MELM-PSO/GA models, PSO

presents a quicker convergence to achieve its best solution than the GA optimizer. From iteration #120, the MELM-PSO performs better than the MELM-GA in terms of prediction accuracy. All in all, the MELM-PSO/GA models are found to present higher forecast accuracy than those of the LSSVM-PSO/GA. In addition, the PSO optimizer is found to be more efficient in reaching the optimal solution for both networks, the MELM and the LSSVM, when compared to the GA optimizer.

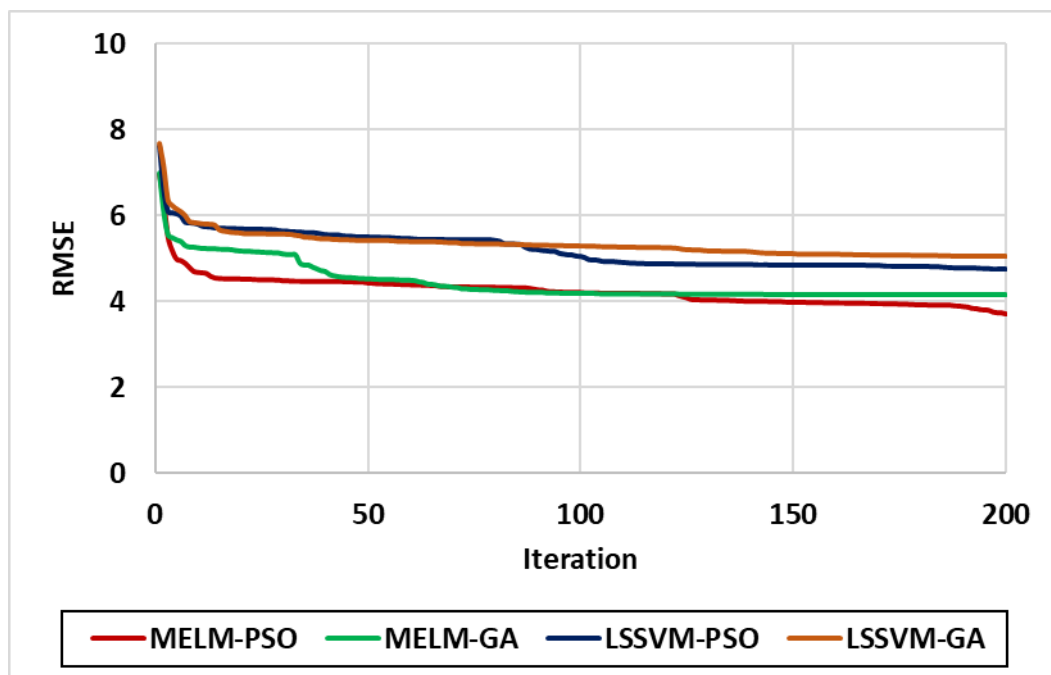


Fig. 14. RMSE values for the training subset based on HML algorithms (MELM-PSO, MELM-GA, LSSVM-PSO, and LSSVM-GA) developed for the prediction of Q_g during supervised learning from the Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami).

To determine the degree of influence of each input variable on Q_g , Spearman's non-parametric correlation coefficient (ρ) is used [97]. The range of this parameter is between -1 (complete negative correlation) to 1 (complete positive correlation), which

indicates a relatively low or high impact [98]. The Spearman parameter equation (Eq. (14)) is defined as follows:

$$\rho = \frac{\sum_{i=1}^n (E_i - \bar{E})(F_i - \bar{F})}{\sqrt{\sum_{i=1}^n (E_i - \bar{E})^2 \sum_{i=1}^n (F_i - \bar{F})^2}} \quad (14)$$

Where E_i is E input variable value of data record i , \bar{E} is mean value for variable E , F_i is F dependent variable (Q_g) value of data record i , \bar{F} is mean value for dependent variable F , and n is the number of input parameters.

Fig. 15 shows the calculated ρ value for the total of 1009 processed learning datasets. Based on the correlation coefficients determined, it is observed that D_{64} , P_d , P_u , and T parameters positively influence Q_g , whereas GLR and γ_g parameters present a negative influence on it. The greatest positive influence on Q_g is observed for D_{64} , while the greatest negative influence is presented by GLR (see in Eq. (15)). In general, the order of input variables' influence degree on Q_g is as follows: choke diameter (D_{64}) > downstream pressure (P_d) > gas-liquid ratio (GLR) > upstream pressure (P_u) > temperature (T) > gas gravity (γ_g).

$$Q_g \propto (D_{64}, P_d, P_u, T) \quad \text{and} \quad Q_g \propto \frac{1}{(GLR, \gamma_g)} \quad (15)$$

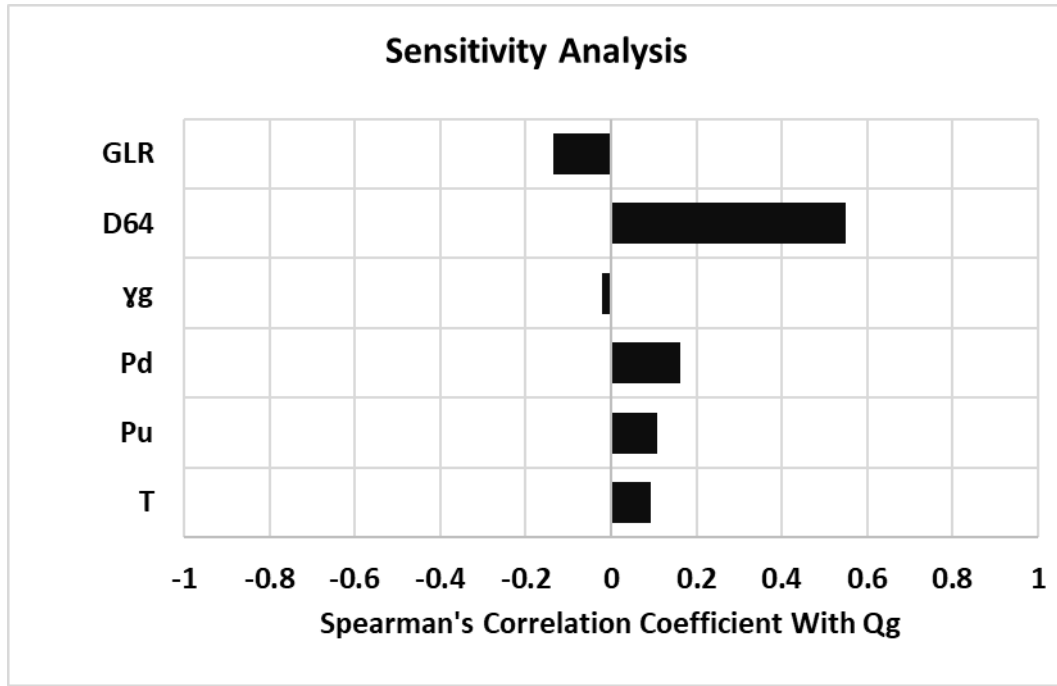


Fig. 15. Input variables assessed based on Spearman's non-parametric correlation coefficient values for Q_g prediction calculated for 1009 data records of supervised learning dataset (from Iranians condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami)).

5. Conclusion

In this research, 1009 input data from Iranian condensate fields (Marun-Khami, Aghajari-Khami, and Ahvaz-Khami) are used to construct four models to predict gas flow rate (Q_g) through six input variables. The input variables to the developed models are temperature (T), the upstream pressure (P_u), downstream pressure (P_d), gas gravity (γ_g), choke diameter (D_{64}), and gas-liquid ratio (GLR). This is the first-ever research work constructing a model based on these variables.

Hybrid machine learning algorithms have several advantages over simple machine learning algorithms. For instance, when the predictive machine learning algorithms are combined with the PSO algorithm to determine control parameters of the algorithms,

the computational speed and accuracy enhance remarkably. In the case of the MELM model, they are optimized in two steps. The first step is to determine the number of hidden layers and neurons in the network. The next is to identify the desired weight and biases applied to those layers and neurons. In the case of LSSVM, the optimization setting is done in one step for the development of LSSVM with PSO/GA optimizer, which ultimately leads to LSSVM-PSO and LSSVM-GA hybrid machine learning optimizer algorithms.

Coupling the PSO to the GA algorithm is an effective approach in achieving high prediction accuracy in the HML algorithms. The multi-hidden layer extreme learning machine (MELM) algorithm coupled with the PSO optimizer presents the best performance. This algorithm uses two hybrid stages with PSO to improve its performance. This algorithm (MELM) first reduces the number of layers and nodes in each hidden layer by combining with PSO. In combination with the second PSO, determines the appropriate weight and bias for the nodes of the selected hidden layers.

The performance accuracy obtained by the MELM-PSO model applied to the total subset entered is $RMSE = 2.8639$ MS_{cf}/Day and $R^2 = 0.9778$, which is significantly higher than the prediction accuracy of empirical equations and HML models. The best performance accuracy obtained from Empirical equations related to Ghorbani et al., Which is $RMSE = 24.2663$ MS_{cf} / Day and $R^2 = 0.4905$. Comparing the developed MELM-PSO model with the previous empirical (Table 1), the AI models (Table 2) suggest that the MELM-PSO model has superior prediction performance and higher accuracy.

Sensitivity analysis obtained from the Spearman coefficient model demonstrates that the input variables, including D_{64} , P_d , P_u , and T , have positive correlations with Q_g . In

contrast, GLR and γ_g parameters present negative correlations with Q_g . D_{64} displays the greatest positive correlation with Q_g , whereas the poorest negative correlation with Q_g is observed for GLR.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

ANN	=	Artificial Neural Network
ANFIS	=	Adaptive Neuro-Fuzzy Inference System
b	=	Bias vector
BP	=	Backpropagation
CF	=	Cost Function
CFD	=	Cumulative distribution functions
$c1$	=	Positive cognitive coefficient (individual learning factors PSO)
$c2$	=	Positive social coefficient (global learning factor for PSO)
d	=	The degree of polynomial
D_{64}	=	Choke size
DL	=	Deep learning
\bar{E}	=	Mean value for variable E
E_i	=	Input variable value of data record i
ELM	=	Extreme Learning Machine
\bar{F}	=	Mean value for dependent variable F
F_i	=	Input variable value of data record i
FN	=	Functional Network
GA	=	Genetic algorithm
G_b	=	The global best value found in the swarm

GEP	=	Gene expression programming
GLR	=	Gas to liquid ratio
LSSVM	=	Least Squares Support Vector Machine
M, I, O	=	Experimental coefficients
MELM	=	Multiple Extreme Learning Machine
MLP	=	Multi-Layer Perceptron
N	=	Number of samples in dataset
n	=	Number of inputs parameters
PSO	=	Particle swarm optimization
P_b	=	The cognitive best value of particle
P_{wh}	=	Wellhead pressure
P_d	=	Downstream pressure
P_u	=	Upstream pressure
Q_g	=	Gas flow rate
Q_{liq}	=	Rate of liquids production
RBF	=	Radial basis function
RMSE	=	Root mean square error
SVM	=	Support Vector Machines
T	=	Transpose matrix
t	=	The intercept of polynomial
y_i	=	Output vector
V_i	=	Particle ith velocity in PSO swarm
W	=	Inertial weight (PSO)
w	=	Weight vector
a_i	=	Lagrangian function multiplier
e_i	=	Regression error
X_i	=	Particle i th position in PSO swarm
x_i	=	Input variable
σ^2	=	The variance of Gaussian kernel
γ	=	Adjustable factor
Δp	=	Differential pressure
θ and k	=	Bias and scale parameters
$\phi(x_i)$	=	Kernel function

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