Predicting Oil Well Gas Lift Performance and Production Optimization Using hybrid Particle Swarm Optimization and Fuzzy Support Vector Machines

[1]Odedele T. O, [2]Ibrahim H. D

Abstract-**This paper considers an approach to design a hybrid Particle Swarm Optimization Fuzzy Support Vector Machines (PSOFuzzySVM) to predict oil well gas lift performance and production optimization in a reservoir. The performance of a production well is a function of several variables. Examples of these variables are Productivity index, Tubing depth, Bottom Hole Flowing Pressure, Tubing Head Pressure, Gross liquid rate tubing size and choke size. Changing any of the variables will alter the performance of the well. In continuous gas lift, gas injection pressure has a decided effect on the efficiency and operation of gas lift. Selection of a gas injection pressure that is too high can result in excessive investment in compression and other equipment, whereas low pressure can cause inefficient gas lift operation and failure to produce a well at full potential. Therefore, the determination of an optimal gas injection pressure is crucial to achieving the most profitable operation. The conventional methods of predicting well performance are many and include Poettmann and Carpenter, Baxendel, Baxendell and Thomas, Ros and Gilbert mathematical and graphical models. This paper discusses the determination of an optimal injection pressure, optimal Gas Liquid Ratio, compressor horsepower and injection rate for a continuous gas lift installation which yields the maximum oil production rate using particle swarm optimization approach. The Fuzzy Support Vector Machines (FuzzySVM), which is a method of a rule-based system extracted from SVM, was also developed for the oil well performance prediction. The motivation of the proposed method is the fact that the system neither requires the determination of number of rules in advance nor requires mathematical computation of inflow, vertical lift and choke performance but utilized extraction of knowledge from corporate databases. Simulation results demonstrate how the designed Particle Swarm Fuzzy support vector machines perform well production prediction. The paper therefore illustrates how Fuzzy support vector machines can be used to generate fuzzy rules from SVM for the purpose predicting the flow rate, as a vital parameter in determining the well performance.**

Index Terms: **Support Vector Machines, Fuzzy Logic, Fuzzy Support Vector Machines, Oil well performance, Particle swarm optimization, choke size, Tubing Head Pressure, Productivity index, Fuzzy rules, Production rate**

.Correspondences
[1,2]Raw Materials Research & Development Council,(RMRDC) Abuja Nigeria
[1]email-odedelermrdc@yahoo.comDeputyDirector(Computer Services Division)
[2]email-hdibrahim2002@yahoo.co.uk Director General of Raw Materials Research & Development Council,(RMRDC)

I. INTRODUCTION

In a naturally flowing well the energy stored in the reservoir to flow the produced fluid to the surface also decreases with time. Reservoir pressure and formation gas provide this energy in the flowing well. As a result of reduction of this energy, oil production rate from a production well also decreases with respect to time such that after some time it may reach an unprofitable level. When reservoir energy is too low for natural flow, or when the desired production rate is greater than the reservoir energy can deliver, it becomes necessary to put the well on some form of artificial lift. As of 2006, 90 % of the world’s oil wells are on some form of artificial lift according to Oilfield Review [1]. When an oil well flows naturally initially, it implies that the pressure at well bottom is sufficient to overcome the pressure losses in the well and flow line to the separator. In a situation where this condition can no longer be met due to decrease in bottom hole pressure, or pressure losses in the well become too great, the natural flow stops and the well eventually dies. The increased pressure losses in the well can as a result of increased overall density due to decreased gas production, increased water cut or mechanical problems like down hole restrictions (scale etc). In the present paper, an attempt is made to extract exact and fuzzy rules from the support vectors out of the trained datasets gas lift performance prediction. The paper also discussed the application of Particle Swarm Optimization(PSO) for design optimization of continuous gas lift. Fuzzy logic has main disadvantage of “Curse of dimensionality” for high dimension input space. The hybrid FuzzySVM was proposed to proffer solution to this shortcoming. The motivation is the ability to predict oil well performance using the information gathered in various operational databases of the company. A model is derived from the trained dataset using SVM and fuzzy rules are extracted for oil well performance prediction purposes.

II. OVERVIEW OF SUPPORT VECTOR MACHINES

Vapnik[2] proposed the support vector machines(SVMs) which was based on statistical learning theory. The governing principles of support vector machines is to map the original data x into a high dimension feature space through a non-linear mapping function and construct hyper plane in new space. The problem of regression can be represented as follows. Given a set of input-output pairs Z =

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{(x1, y1), (x2, y2), . . . ,(xℓ, yℓ)}, construct a regression function f that maps the input vectors x € X onto labels y € Y . The goal is to find a classifier f €F which will correctly predict new samples. There are two main cases to consider when we use a separating hyper-plane:
1. A linearly separable case
2. The data might not be linearly separable.
SVMs tackle the first problem by finding the hyper-plane that realizes the maximum margin of separation between the classes. [2] A representation of the hyper-plane solution used to classify a new sample xi is:

$$Y=f(x)=wi\phi(x)+b \qquad (1)$$

Where wi,ϕ(x) is the dot-product of the weight vector w and the input sample, and b is a bias value. The value of each element of w can be viewed as a measure of the relative importance of each of the sample attributes for the prediction of a sample. Various research studies have shown that the optimal hyperplane can be uniquely constructed through the solution of the following constrained quadratic optimization problem [3,4]

$$\text{Minimise} 1/2\|w\|+C\sum_{i=1}^{l} \xi_I \; (2a)$$

subject to _ $y_i(\|w\|+ b) \geq 1 - \xi i$, i= 1, . . . , ℓ
$\xi i \geq 0, i=1,...,\ell$ (2b)
In linearly separable problem, the solution minimizes the norm of the vector w which increases the flatness(or reduces the complexity) of the resulting model and hence the generalization ability is improved. With non-linearly separable hard-margin optimization, the goal is simply to find the minimum ||w|| such that the hyperplanef(x) successfully separates all ℓ samples of the training dataset. The slack variables ξi are introduced to allow for finding a hyperplane that misclassifies some of the samples (soft-margin optimization) because many datasets are not linearly separable. The complexity constant C >0 determines the trade-off between the flatness and the amount by which misclassified samples are tolerated. A higher value of C means that more importance is attached to minimizing the slack variables than to minimizing||w||. Instead of solving this problem in its primal form of (2a) and (2b), it can be more easily solved in its dual formulation by introducing Langrangian multiplier α [3,4]:
Maximize $W(\alpha)=\sum_{i=1}^{l} \alpha i+½\sum_{i,j=1}^{l} \alpha i\alpha jyiyj\langle xi, xj\rangle$ (3a)
Subject to $C\geq\alpha i\geq 0,\sum_{i=1}^{l} \alpha iyi=0$ (3b)
In this solution, instead of finding w and b the goal now is find the vector α and bias value b, where each αi represents the relative importance of a training sample I in the classification of a new sample. To classify a new sample, the quantity f(x) is calculated as:
$f(x)=\sum_{i=1}^{sv} \alpha iyiK\langle xi, xj\rangle+b$ (4)
where b is chosen so that yif(x) = 1 for any I with C > αi>0. Then, a new sample xs is classed as negative if f(xs) is less than zero and positive if f(xs) is greater than or equal to zero. Samples xi for which the corresponding αi are non-zero are called as *support vectors* since they lie closest to the separating hyperplane. Samples that are not support vectors have no influence on the decision function.
Training an SVM entails solving the quadratic programming problem of (3a) and (3b). There are many standard methods that are be applied to SVMs, these include the Newton method, conjugate gradient and primal-dual interior-point methods, but this study used the Sequential Minimal Optimization. [5]. In SVMs, kernel functions are used to map the training data into a higher dimensional feature space via some mapping φ(x) and construct a separating hyperplane with maximum margin. This yields a non-linear decision boundary in the original input space. Typical types of kernels are:
− Linear Kernel: $K(x, z) = \langle x, z\rangle$
− Polynomial Kernel: $K(x, z) = (1 + \langle x, z\rangle)^d$
− RBF Kernel: $K(x, z) = \exp(-\|x-z\|^2/2\sigma 2)$
− Sigmoid Kernel: $K(x, z) = \tanh(\gamma^*\langle x, z\rangle - \theta)$
This condition ensures that the solution of (3a) and (3b) produces a global optimum. The functions that satisfy Mercer's conditions can be as kernel functions. As promising as SVM is compared with ANN as regards generalization performance on unseen data, the major disadvantage is its black box nature. The knowledge learnt by SVM is represented as a set numerical parameters value making it difficult to understand what SVM is actually computing.

III. FUZZY LOGIC OVERVIEW

Fuzzy Logic which was introduced by Lotfi A. Zadeh was based on fuzzy sets in 1965 [6,7,8]. The basic concept of fuzzy logic is to consider the intermediate values between [0,1] as degrees of truth in addition to the values 1 and 0. The following sections will briefly discuss the general principles of fuzzy logic, membership functions, linguistic variables, fuzzy IF-THEN rules, combining fuzzy sets and fuzzy inference systems (FISs).

A. Fuzzy Inference System

Fuzzy inference systems (FISs) are otherwise known as fuzzy-rule-based systems or fuzzy controllers when used as controllers. A fuzzy inference system (FIS) is made up of five functional components. The functions of the five components are as follows:
1. A *fuzzification is an* interface which maps the crisp inputs into degrees of compatibility with linguistic variables.
2. A *rule base is an interface* containing a number of fuzzy if-then rules.
3. A *database* defines the membership functions (MFs) of the fuzzy sets used in the fuzzy rules.
4. A *decision-making* component which performs the inference operation on the rules.
5. A *defuzzification* interface which transforms the fuzzy results of the inference into a crisp output. The qualified consequents are combined to produce crisp output according to the defined methods such as: centroid of area, bisector of area, mean of maximum, smallest of maximum and largest of maximum etc. This final step is also known as defuzzification[9,10,11,12]. The major disadvantage of standard fuzzy logic is the curse of dimensionality nature for high dimensional input space. For instance, if each input variable is allocated m fuzzy sets, a fuzzy system with n inputs and one output needs on the order of m^n rules.

IV. EXTRACTING FUZZY RULES FROM SUPPORT VECTOR MACHINE

In this fuzzy SVM section, we will first give an insight into how to extract fuzzy rules from Support Vector Machine (SVM), and then explain the process of optimizing the fuzzy rules system and highlight an algorithm that will convert

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SVM into interpretable fuzzy rules. This method has both good generalization performance and ability to work in high dimensional spaces of support vector machine algorithm with high interpretability of fuzzy rules based models. As mentioned earlier, Support vector machine (SVM) is a useful method of classifying dataset. This is a new machine learning method based on the Statistical Learning.

Suppose a set of training dataset denotes the input space patterns. Their main concept is to construct a hyperplane that acts as a decision space such that the margin of separation between positive and negative samples is maximized. This is generally referred as the Optimal Hyperplane". This property is achieved as the support vector machines are an approximate implementation of the method of structural risk minimization[13]. Despite the fact that a support vector machine does not provide domain-specific knowledge, it provides good generalization ability, a unique property among the different types of machine learning techniques. Instead of solving this problem in its primal form of (2a) and (2b), it can be more easily solved in its dual formulation by introducing Langrangian multiplier α [14]: as highlighted in section II. The crucial step in fuzzy SVM is to build a reliable model on training samples which can correctly predict class label and extract fuzzy rules from SVM. On the other hand, fuzzy rule-base which consists of set of IF-THEN rules constitutes the core of the fuzzy inference [13,14,15]. Suppose there are m fuzzy rules, it can be expressed as following forms:

Rule j: If x_1 isAj^1 AND x_2 isAj^2 AND ………$x_n$is. Aj^n THEN bj (5)

Where x_k is the input variables; b_j is the output variable of the fuzzy system; and A^k are linguistic terms characterized by fuzzy membership functionsa_j^k. If we choose product as the fuzzy conjunction operator, addition for fuzzy rule aggregation, and height defuzzification, then the overall fuzzy inference function is

$$F(x) = \frac{\sum_{j=1}^{m} bj \prod_{k=1}^{n} a_j^k(xk)}{\sum_{j=1}^{m} \prod_{k=1}^{n} a_j^k(xk)} \quad (6)$$

Where F(x)
is the output value when the membership function achieves its maximum value.

If on the other hand, the input space is not wholly covered by fuzzy rules, equation(5) may not be defined. To avoid this situation, Rule0 can be added to the rule base

Rule0: If $A0^1$ AND $A0^2$ AND ………. $A0^n$ THEN b0

$$F(x)=\frac{b0+\sum_{j=1}^{m} bj \prod_{k=1}^{n} a_j^k(xk)}{1+\sum_{j=1}^{m} \prod_{k=1}^{n} a_j^k(xk)} \quad (7)$$

In a binary classification, sign(F(x)) shows the class label of each input x and since the denominator is always positive, class label of each input is computable by

$$Label(x) = sign(b0 + \sum_{j=1}^{m} bj \prod_{k=1}^{n} a_j^k(xk) \quad (8)$$

In order to let equation (4) and (8) are equivalent, at first we have to let the kernel functions in (4) and the membership functions in (8) are equal. The Gaussian membership functions can be chosen as the kernel functions to satisfy the Mercer condition[13, 14, 15]. Besides, the bias term of the expression (4) should be zero. If the Gaussian function is chosen as the kernel function and membership functions, and the number of rules equals the number of support vectors then (4) and (8) becomes equal and then output of fuzzy system (8) is equal to the output of SVM (4). A membership function $\boldsymbol{\mu}(x)$ is reference function if and only if $\boldsymbol{\mu}(x)=\boldsymbol{\mu}(-x)$ and $\boldsymbol{\mu}(0)=1$. A reference function with location transformation has the following property for some locations m_j€R

$$a_j^k(xk) = a^k(x_k - m_j^k)$$

A translation invariant kernel k is given by

$$K(x,m_j)=\prod_{k=1}^{n} a^k(x_k - m_j^k)$$

Examples of reference functions are as shown in Table I

Table I.
REFERENCE FUNCTIONS

	Reference functions
Symmetric Triangle	$\boldsymbol{\mu}(x)=Max(1- g\,\lvert x\rvert,0) \quad g>0$
Gaussian	$\boldsymbol{\mu}(x)=e^{-gx^2}\, g>0$
Cauchy	$\boldsymbol{\mu}(x)=\frac{1}{1+gx^2}\, g>0$
Laplace	$\boldsymbol{\mu}(x)=e^{-g\lvert x\rvert}\, g>0$
Hyperbolic Secant	$\boldsymbol{\mu}(x)=\frac{2}{e^{g\lvert x\rvert}+e^{-g\lvert x\rvert}}\, g>0$

V. OVERVIEW OF PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is an evolutionary computation technique, first introduced by Kennedy and Eberhart.[16,17,18,19,20] The main idea is used to model a group social behavior such as the way birds travel when trying to find sources of food, or fish schooling. In PSO, there are no operators inspired by natural evolution applied to extract a new generation of possible solutions. Instead of mutation, the behavior is modeled in such way is that the "particles" inside the "swarm" (or population) are treated as solutions to a given problem with exchange of information. And as such, each particle will adjust its movement towards its own previous best position and global best previous position. The flowchart of the method is given in Fig. 1. c1 and c2 are two positive constants, called the cognitive and social parameter respectively; r_{i1} and r_{i2} are random numbers uniformly distributed within the range [0, 1]. In each iteration, Eq. (9) is used to determine the i-th particle's new velocity, while Eq. (10) provides the new position of the i-th particle by adding its new velocity, to its current position. The performance of each particle is measured according to a fitness function, which depends on the problem. In optimization problems, the fitness function is usually identical with the objective function under consideration. The role of the inertia weight w is considered important for the PSO's convergence behavior. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. Thus, the parameter w regulates the trade-off between the global (wide-ranging) and the local (nearby) exploration abilities of the swarm. A large inertia weight facilitates exploration (searching new areas), while a small one tends to facilitate exploitation, i.e.

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fine-tuning the current search area. A proper value for the inertia weight w provides balance between the global and local exploration ability of the swarm, and, thus results in better solutions. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest. After finding the two best values, the particle updates its velocity and positions with following equations (9) and (10).

v[n+1] = v[n] + c1 * rand() * (pbest[n] - X[n]) + c2 * rand()*(gbest[n]-X[n]) (9)

X[n+1]=X[n]+v[n+1] (10)

v[n] is the particle velocity, X[n] is the current particle (solution). pbest[n] and gbest[n] are defined as stated before.

rand () is a random number between (0,1). c1, c2 are learning factors. usually c1 = c2 = 2.
The procedure describing proposed PSO approach is as follows.
1.Initializing PSO with population size, inertia weight and generations.
2. Evaluating the fitness of each particle.
3. Comparing the fitness values and determines the local best and global best particle.
4. Updating the velocity and position of each particle till value of the fitness function converges.

VI. METHODOLOGY

The system is divided into two parts: as it makes use of different systems for gas lift design optimization and prediction of gas lift performance.

a. Gas lift design and production optimization using Particle Swarm Optimization(PSO).
b. Predictions of gas lift performance using FuzzySVM

In order to analyze the performance of a completed flowing well, it is important to recognize three different components which are linked together. These components are the inflow performance, the vertical lift performance and the choke performance[21,22,23,24]. The inflow performance represents the flow of oil, water and gas in porous media into the bottom of the well. The vertical lift performance involves the analysis of pressure two-phase mixture of gas and liquid.
The inflow performance represents the flow of oil, water and gas in porous media into the bottom of the well. The vertical lift performance involves the analysis of pressure two-phase mixture of gas and liquid.
In mathematical formulation, gas lift performance can be modeled as a two parameter family of ordinary differential equation (ODE) representing the energy equation along the tubing.

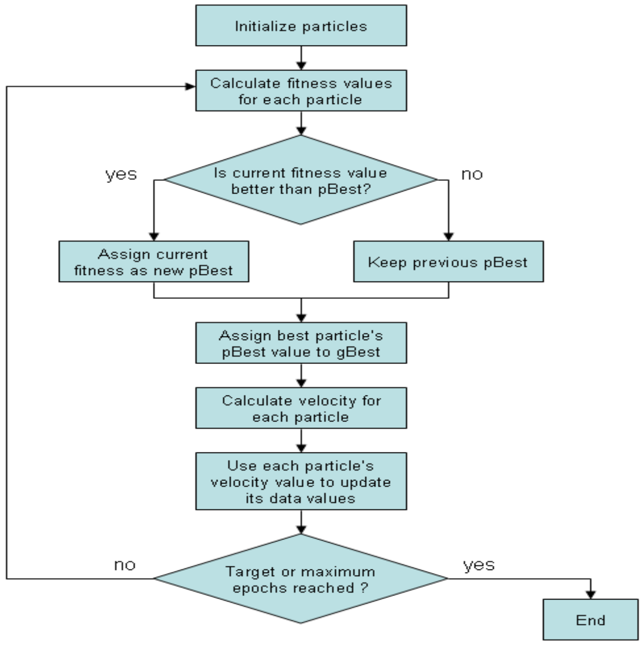

Fig1. Flow diagram illustrating the particle swarm optimization algorithm

$$144\frac{\Delta p}{\Delta h} = \bar{\rho} + \frac{K}{\bar{\rho}} \quad (11)$$

with initial conditions
$P(0) = P$wh,
where $\bar{\rho}$=overall density of fluid column in the tubing Ib/ft^3
Δp =Pressure drop over vertical interval Δh, ft

$$\bar{K}=\frac{fq^2M^2}{7.413x10^{10}D^5} \quad (12)$$

q=Liquid production rate bbl/day
M= total mass of gas and liquid associated with 1 bbl of stock tank liquid (Ib)

D= Inside diameter of the tubing ft
f= Energy loss factor

Similarly, the Inflow Performance Relationship(IPR) is expressed as

$$J=\frac{q}{\Delta P} \quad (13)$$

where J=Productivity Index bbl/day.Psi

ΔP =Pws-Pwf
Pws=Reservoir pressure, psi Pwf=Bottom-hole flowing pressure, psi The values of q and Pwf are obtained from the solutions of the equations(11) and (13).
As expected, the compressor horsepower decreases as injection pressure increases and the cost of a compressor installation naturally goes up with the horsepower. Part of the objectives of this paper is to use the concept of particle swarm optimization to obtain an optimal injection pressure, Gas injection rate, compressor horse-power and GLR that will facilitate a more profitable gas lift installation [25,26,27,28,29,30].

The expression for compression horsepower is given by equation (14)

$$\text{Power}=0.223M\{(P_2/P_1)^{0.2}-1\}\ \text{hp} \quad (14)$$

where hp=horse power
M=Gas rate mcf/day at standard conditions.

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P_1=Compressor input pressure, Psia
$P_{2=}$ Compressor output pressure, Psia (Injection Pressure)
M=q(optimum GLR-formation GLR) (15)
A numerical scheme based on particle swarm optimization is constructed. Computation procedure could be written as follows: Using 4th order Runge Kutta method, ΔP could be computed from equation(11) and using equation(13) q and Pwf are obtained [31].

Step1: Initializing PSO with population size, inertia weight

Step 2: Compute fitness of each particle using equations(14) & (15)
Step 3: Obtain P_{best} and $G_{best}$for each particle
Step 4: Update P_2 and optimum GLR using(9)&(10)
Step 5: Return to step 2 until convergence criteria are satisfied

VII. APPLICATION EXAMPLE

This section gives an example of continuous gas lift design. Consider a well with characteristics as shown in TableII.

Table II
TYPICAL CONTINUOUS GAS LIFT DESIGN WELL DATA

Well Depth (ft)	5000.00
Tubing size (in)	2.5
WOR	0.2
Producing GOR	650
Oil Production rate (q) bbl/day	302
Water gravity	1.15
Oil gravity	42.3
Gas gravity	0.816
Water Gravity	0.1
Productivity Index(J) bbl/day*Psi	0.333
Reservoir Pressure Psi	2500
Compressor input pressure, Psi	150
Tubing Head Pressure THP	150
Surface Temperature ^{0}F	70
Bottom Hole Temperature ^{0}F	200
Oil formation volume factor (B_o)	1.25

It is required to determine an optimum gas injection pressure that will optimize gas injection rate in order to obtain maximum production rate.

VIII. RESULTS AND DISCUSSION

Here, some numerical results are shown for hypothetic data which is given in Table III. The following are computational results using Particle Swarm Optimization Algorithm. The computation process is conducted for two hundred generations with the numerical optimum points given in Table III.

Table III.
RESULTS USING PARTICLE SWARM OPTIMIZATION

Injection Pressure	GLR	GasInjection Rate scf/day	HorsePower
1761.0594	7536.19	1612247.6362	211.1198
1705.9680	2854.30	610553.90	67.7998
1645.1764	9797.95	2096152.36	270.0864
1686.9164	6693.93	1432046.019	181.4530
1799.0081	8761.33	1874367.58	251.0575
1767.6094	8352.17	1786827.48	236.3530
1699.0185	7299.478	1561603.04	200.1832
1604.1212	5921.34	1266749.28	154.3676
1797.5579	3674.55	786046.60	94.8267
1668.0494	1273.55	272351.43	20.3321
1739.4542	5546.16	1186480.13	149.7240
1756.2504	9163.88	1960493.46	260.1894
1634.0085	2321.43	496545.36	50.7229

The results in Table III., show that the optimal parameters for the gas lift installation are: Injection pressure=1668.05Psi. GLR=1273.55Scf/Stb, Gas Injection rate=272351.43Scf/day, Horsepower=20hp
The sample data used for training are as shown in Table IV while those samples for testing are as shown in Table V. The proposed model shows a high accuracy in predicting production rate with a stable performance, and achieved lowest root mean square error.
The results of testing (external validation check were summarized in Table VI. The predicted production rate is as listed in Table VII. We observe from these results that the hybrid Fuzzy-support vector machines modeling scheme performs satisfactorily for predictive correlations.
A plot of the experimental and predicted data versus the input data is as shown in Fig 2. The study develops a fuzzySVM to predict gas lift performance. The membership functions for a regression fuzzySVM are restricted to a category of membership functions generated from location transformation of reference function. higher potential to increase accuracy drastically. The predictive accuracy is 90.9% with complexity parameter C=1.35, gamma=2.0 and RMSE=26.4

A. *PSO Parameters for Gas Lift Problem*

C1=1.2, C2=0.8, w=0.5, number of particles=20, iterations=200
Fitness function=Power=0.223M$\{(P_2/P_1)^{0.2}$-1} hp
M=q(optimumGLR –formationGLR)

Table IV
TRAINING SAMPLES

Well Name	Reservoir Name	Productivity Index	Tubing Head Pressure	GLR	Choke	Pressure	Gas Injection Rate scf/day	Production Bbl/d
Eyak2	Eyak	0.4	100	0.27	46	2200	472350	130
Eyak2	Eyak	0.3	235	0.27	21.5	2000	420400	140
Eyak2	Eyak	0.4	170	0.4	44	2000	280100	170
Etim1	Etim	0.3	235	0.27	21.5	2000	420250	210
Eyak2	Eyak	0.54	170	0.8	46	1380	190150	260
Eyak2	Eyak	0.4	400	0.8	27	1820	290150	180
Eyak3	Eyak	0.3	235	0.27	21.5	2000	260340	310
Eyak2	Eyak	0.35	100	0.75	46	2000	150260	150
Eyak2	Eyak	0.3	235	0.27	21.5	1900	250000	230
Eyak2	Eyak	0.45	200	0.2	45	1950	295200	220

Table V
TESTING SAMPLES

Well Name	Reservoir Name	Productivity Index	Tubing Head Pressure	GLR	Choke	Pressure	Gas Injection Rate scf/day	Production Bbl/d
Eyak2	Eyak	0.4	100	0.27	46	2200	472350	130
Eyak2	Eyak	0.3	235	0.27	21.5	2000	420400	140
Eyak2	Eyak	0.4	170	0.4	44	2000	280100	170
Etim1	Etim	0.3	235	0.27	21.5	2000	420250	210
Eyak2	Eyak	0.54	170	0.8	46	1380	190150	260
Eyak2	Eyak	0.4	400	0.8	27	1820	290150	180
Eyak3	Eyak	0.3	235	0.27	21.5	2000	260340	310
Eyak2	Eyak	0.35	100	0.75	46	2000	150260	150
Eyak2	Eyak	0.3	235	0.27	21.5	1900	250000	230
Eyak2	Eyak	0.45	200	0.2	45	1950	295200	220
Eyak2	Eyak	0.55	100	0.3	45	2150	200190	?
Eyak2	Eyak	0.4	150	0.25	36	2050	270340	?
Eyak2	Eyak	0.35	200	0.2	44	2000	540240	?

Table VI
GAS LIFT PERFORMANCE PREDICTION RESULTS

Method	Samples	Fuzzy rules	C	Gama	RMSE	Accuracy%
SVM	11	7	1.35	2.0	109.3	45.98
Fuzzy SVM	11	7	1.35	2.0	26.4	90.9

Table VII.
PREDICTED PRODUCTION RATE(FUZZYSVM)

Gas Injection rate scf/day	Production rate bbl/day
200190	132.86
270340	205.57
540240	70.91

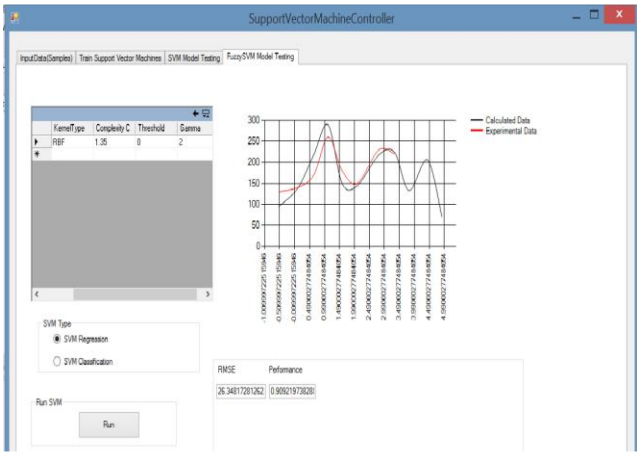

Fig 2. A plot of the experimental and predicted data versus the input data

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Dr Ibrahim Doko Hussaini who hails from Doko Niger state of Nigeria was born on 23rd September 1962. The educational background is as follows:* The University of Leeds, United Kingdom (1993)Ph.D (Textile Science Engineering). He is currently Director General of Raw Materials Research & Development Council,(RMRDC) , Abuja Nigeria

EngrTimothy.O Odedele who hails from Ipetumodu, Osun state of Nigeria was born on 29th April 1958. The educational background is as follows: * B.Sc. Petroleum Engineering (Second class Upper Division1984) University of Ibadan, Ibadan,* M.Sc Computer Science -University of Ibadan, Ibadan. He is currently Deputy Director(Computer Services Division) with Raw Materials Research &Development Council, Abuja Nigeria