Detection of Oil Production Abnormalities in a Cluster of Wells System Using Fuzzy Support Vector Machines

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***Abstract*—Efficient methods for detecting oil production abnormalities have been active research area in recent years. This paper presents an hybrid approach towards the detection of oil production abnormalities using Fuzzy Support Vector Machine (FuzzySVM). The main motivation of this study is the identification of wells having low production occasioned by formation damage resulting from either fluid invasion during the process of drilling or introduced by various mechanisms while producing. This hybrid FuzzySVM model preselects suspected wells to be inspected for selection for well stimulation based on abnormal production behavior. The proposed approach uses well production profile information and well tests results to expose abnormal behavior. The result of the abnormalities detection model yields classified classes that are used to shortlist potential formation damage suspects for possible well stimulation such as hydraulic fracturing or acidizing. Simulation results proved that the proposed method is more effective in detecting wells having abnormal low production.**

***Index Terms*—Support vector machine, FuzzySVM, Formation damage, Low production, production profile, Well stimulation**

I. INTRODUCTION

Oil and gas operations involve a wide range of activities which include exploration, drilling and production. Reservoir stimulation is one of the main activities aimed at increasing oil production rate and ultimate economic recovery. [1]

Once a well has low production problem, there are vital questions to be answered by the production team. How can the identified problems be eliminated?

How can such problem be detected or identified? How can well be selected for stimulation by either acidizing or hydraulic fracturing or do we have to consider drilling a new well to compensate for reduction in production?

Formation damage caused by either fluid invasion during drilling process through the reservoir or introduced by various mechanism while producing the reservoir, represents an obstacle to optimum oil production.

In recent years, several computational intelligent research studies for prediction techniques have been carried out in the field of petroleum production. [2][3][4] Among these, support vector machines is one of the most widely used which defined the pattern of oil production of a well over a period of time.[5]

At present, well testing activities are carried out for evaluating rock and fluid properties but there is non-availability of a system for short listing possible low production suspects. The approach proposed in this paper provides an intelligent system for assisting production teams to increase effectiveness of their operation in detecting low production wells based on production profiles of wells derived from the well database. This system will facilitate production abnormality detection hit-rate for onsite well stimulation.

This paper presents a novel framework to detect low oil production i.e., well with abnormal production patterns indicating possible formation damage. An hybrid combination of fuzzy rule based inference system and Support Vector Machines (SVMs) is used to identify wells having production problems. This study uses experimental historical well data collected from oil fields. Well production patterns are extracted using data mining techniques, which represent well production profiles. Based on the assumption that production profiles contain abnormalities when low production occurs, Fuzzy SVM classifies production profiles of wells for detection of possible formation damage. There are several different types of abnormalities that can occur, but our research concentrates only on scenarios where abrupt low production changes appear in production profiles, indicating formation damage.

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II. OVERVIEW OF SUPPORT VECTOR MACHINES

Vapnik[6] 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 classification can be represented as follows. Given a set of input-output pairs Z = {(x1, y1), (x2, y2), . . . , (xℓ, yℓ)}, construct a classifier function f that maps the input vectors x € X onto labels y € Y . In binary classification the set of labels is simply Y = {−1, 1}. The goal is to find a classifier f F which will correctly classify 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. [7][8][9] 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 classification 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 [7][8][9]

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

$$\text{subject to \_ } yi(\|w\|+ b) \geq 1 - \xi i,\ i = 1, \ldots, \ell$$
$$\xi i\geq 0, i=1,\ldots,\ell \qquad (2b)$$

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 hyperplane f(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 optimisation) 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 minimising the slack variables than to minimising ||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 [13]:

$$\text{Maximize } W(\alpha)=\sum_{i=1}^{l} \alpha i+½\sum_{i,j=1}^{l} \alpha i\alpha jyiyj\langle xi, xj\rangle \qquad (3a)$$

$$\text{Subject to } C\geq\alpha i\geq 0,\ \sum_{i=1}^{l} \alpha iyi =0 \qquad (3b)$$

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:

$$f(x)=\sum_{i=1}^{sv} \alpha iyiK\langle xi, xj\rangle +b \qquad (4)$$

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.[10] but this study used the Sequential Minimal Optimization. [11] [12][13]

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 [14] [15][16]. The basic concept of fuzzy logic is to consider the intermediate values betweenl [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

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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.

In fuzzy logic, 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. METHODOLOGY

A. Data Acquisition

Production data from Production Information System (e-PIS) was obtained for 20 wells for a period of 12 months i.e., from June 2007 to June 2008.

B. Data Normalization

The production data needs to be represented using a normalized scale for the SVM classifier. Therefore, the daily average kWh production data was normalized as follows:

Normalized(P) =P-Min(P)/Max(P)-Min(P)

where *P* represents the current production of the well, and *min*(P) and *max*(*P*) represent the minimum and maximum values in the 12 month production feature set. Typical production profiles of wells were then established, with each production profile being represented by the 12 normalized daily average production rate bbl/day features.

All 12 features were given a label, where the labels are represented by integer values [-1,1]. The negative value, -1 indicates normal well while positive value indicates abnormal well.

C. . Extracting Fuzzy Rules From Support Vector Machine

In this 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 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. 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 [19][20]. Suppose there are m fuzzy rules, it can be expressed as following forms:

Rulej: If x_1 is Aj^1 AND x_2 is Aj^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 function sa_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

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

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

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

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

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

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 [23][24]. 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

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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
$K(x,m_j)= \prod_{k=1}^{n} a^k(x_k - m_j^k)$
Eamples of reference functions are as shown in Table 1.0

TABLE 1.
REFERENCE FUNCTIONS

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

A schematic of Fuzzy SVM Oil Well Production abnormalities Detection System is shown in figure.1. The system is designed to detect oil production abnormalities using the production profiles of well clusters in a reservoir.

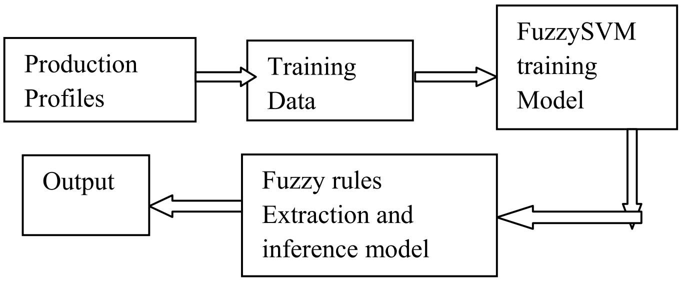

Fig1. Fuzzy SVM Oil Well Production abnormalities Detection System

IV. RESULTS AND DISCUSSION

The sample data used for the training of Fuzzy SVM and testing of model are as shown in Table3. and Table4. respectively. There are two types of errors namely Type I and Type II errors. Type I(false alarm) refers to a situation when normal producing well was classified as abnormal well. Type II error refers to abnormal producing well being classified as normal producing well. The results of testing (external validation check were summarized in Table 2. We observed form these results that the hybrid Fuzzy-support vector machines modeling scheme performed satisfactorily for predictive correlations than traditional SVM. The FuzzySVM model showed a high accuracy in predicting normal class with a stable performance, and achieved the lowest absolute percent relative error typeI and typeII errors, lowest root mean square error, and the highest correlation coefficient among other correlations for the used two distinct data sets. A plot of the experimental and predicted data versus the input data is as shown in Figure 2

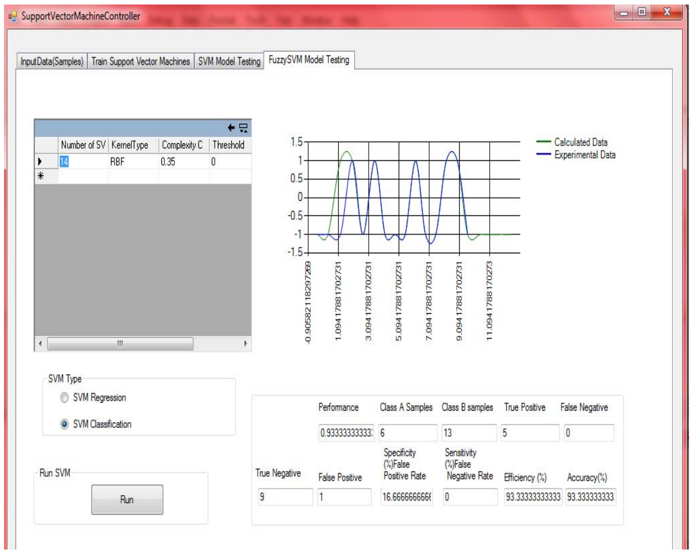

Fig2. Plot of Actual and Calculated Data with C=0.35, Gamma=3.0, Kernel-Gaussian, Membership function- Gaussian

TABLE2
SUMMARY OF THE RESULTS

Method	Number of samples	Type I error	TypeI error	complexity constant C	Gamma	Membership Function	Kernel Function	Accuracy
SVM	15	100%	37.5	0.35	3.0	-	Gaussian	60.0%
FuzzySVM	15	16.7%	0%	0.35	3.0	Gaussian	Gaussian	93.3%
FuzzySVM	15	16.7%	0%	1.0	2.8	Laplace	Laplace	93.3%

VI. CONCLUSION

This study developed a novel fuzzy SVM to detect oil well production abnormalities. The classification of well production(Normal and Abnormal) is a work that is aimed at with an in-depth study and extraction of rules from support vectors. The study and understanding of the fuzzy rule based support vector machines and its roles in classification tasks were done. This technique was then implemented in the Microsoft C# programming language to perform data classification task for the oil well production data set. This approach compensated for the shortcomings of Fuzzy logic and standard SVM. This will benefit oil companies not only in

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TABLE 3
OIL WELL PRODUCTION PROFILE TRAINING DATA

WellName	Month Prod1	Month Prod2	Month Prod3	Month Prod4	Month Prod5	Month Prod6	Month Prod7	Month Prod8	Month Prod9	Month Prod10	Month Prod11	Month Prod12	Y
Eyak1	2.5	2.8	3.28	3.85	3.88	3.19	3.25	4.1	4.5	4.7	4.7	4.8	-1
Eyak2	3.5	3.18	3.56	3.75	3.82	3.92	3.95	4.11	4.15	4.17	4.27	4.38	-1
Eyak3	2.15	2.18	3.18	3.25	3.28	3.39	3.45	4.21	4.25	4.17	4.17	4.28	-1
Eyak4	2.55	2.28	3.38	3.45	3.67	3.49	3.55	4.31	4.15	4.7	4.27	4.03	1
Eyak5	2.75	2.38	3.48	3.55	3.88	3.93	3.95	4.41	4.53	4.77	4.87	4.98	-1
Eyak6	2.85	2.88	3.38	3.45	3.78	3.79	3.85	4.31	4.22	4.17	4.15	4.12	1
Eyak7	2.45	2.78	3.58	3.85	3.85	3.92	3.94	4.1	4.5	4.7	4.7	4.8	-1
Eyak8	2.83	2.88	3.68	3.81	3.86	3.93	3.96	4.42	4.52	4.72	4.76	4.85	-1
Eyak9	2.53	2.58	3.78	3.82	3.87	3.94	3.97	4.43	4.51	4.72	4.77	4.86	-1
Eyak10	2.54	2.68	3.88	3.83	3.89	3.95	3.98	4.44	4.55	4.07	4.02	4	1
Eyak11	2.56	2.78	3.83	3.84	3.85	3.96	3.99	4.46	4.65	4.73	4.75	4.88	-1
Eyak12	2.46	2.88	3.48	3.76	3.78	3.97	4.05	4.47	4.65	4.71	4.73	4.98	-1
Eyak13	2.51	2.72	3.85	3.87	3.88	3.89	4.08	4.48	4.25	4.07	4.02	4.01	1
Eyak14	2.59	2.82	3.56	3.69	3.795	3.92	4.15	4.49	4.15	4.02	4.01	4	1
Eyak15	2.45	2.83	3.47	3.78	3.79	3.91	3.95	4.51	4.57	4.73	4.78	4.87	-1

TABLE4
OIL WELL PRODUCTION PROFILE TESTING DATA

WellName	Month Prod1	Month Prod2	Month Prod3	Month Prod4	Month Prod5	Month Prod6	Month Prod7	Month Prod8	Month Prod9	Month Prod10	Month Prod11	Month Prod12	Y
Eyak1	2.5	2.8	3.28	3.85	3.88	3.19	3.25	4.1	4.5	4.7	4.7	4.8	-1
Eyak2	3.5	3.18	3.56	3.75	3.82	3.92	3.95	4.11	4.15	4.17	4.27	4.38	-1
Eyak3	2.15	2.18	3.18	3.25	3.28	3.39	3.45	4.21	4.25	4.17	4.17	4.28	-1
Eyak4	2.55	2.28	3.38	3.45	3.67	3.49	3.55	4.31	4.15	4.7	4.27	4.03	1
Eyak5	2.75	2.38	3.48	3.55	3.88	3.93	3.95	4.41	4.53	4.77	4.87	4.98	-1
Eyak6	2.85	2.88	3.38	3.45	3.78	3.79	3.85	3.31	3.22	4.17	4.15	4.12	1
Eyak7	2.45	2.78	3.58	3.85	3.85	3.92	3.94	4.1	4.5	4.7	4.7	4.8	-1
Eyak8	2.83	2.88	3.68	3.81	3.86	3.93	3.96	4.42	4.52	4.72	4.76	4.85	-1
Eyak9	2.53	2.58	3.78	3.82	3.87	3.94	3.97	4.43	4.51	4.72	4.77	4.86	-1
Eyak10	2.54	2.68	3.88	3.83	3.89	3.95	3.98	4.44	4.55	4.07	4.02	4	1
Eyak11	2.56	2.78	3.83	3.84	3.85	3.96	3.99	4.46	4.65	4.73	4.75	4.88	-1
Eyak12	2.46	2.88	3.48	3.76	3.78	3.97	4.05	4.47	4.65	4.71	4.73	4.98	-1
Eyak13	2.51	2.72	3.85	3.87	3.88	3.89	4.08	4.48	4.25	4.07	4.02	4.01	1
Eyak14	2.59	2.82	3.56	3.69	3.795	3.92	4.15	4.49	4.15	4.02	4.01	4.01	1
Eyak15	2.45	2.83	3.47	3.78	3.79	3.91	3.95	4.51	4.57	4.73	4.78	4.87	-1
Eyak16	2.5	2.58	3.48	3.85	3.76	3.7	2.95	2.21	2.15	2.1	2	1.8	?
Eyak17	2.51	2.81	3.82	3.85	3.8	3.9	4.95	5.1	4.98	4.87	4.7	4.28	?
Eyak18	2.05	2.81	3.83	3.85	3.87	3.91	3.95	4.12	4.59	4.78	4.79	4.89	?
Eyak19	2	2.82	3.8	3.84	3.85	3.92	3.96	4.01	4.05	4.74	4.78	4.81	?

improving its handling of low production, but will complement their existing ongoing practices, and it is envisaged that tremendous savings will result from the use of the system.

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