A Novel Hybrid Computational Intelligence Model for the Characterization of Oil and Gas Reservoirs

BY

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Dedication

This work is dedicated to ALLAH.

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Firstly, I give thanks to Allah, the Ever-living, Self-subsisting Eternal, for His guidance on my decision to embark on this intellectual journey to KFUPM in Saudi Arabia for the completion of my Master of Science program. He has also guided me through the ups and downs of the program and has crowned it with its successful defense.

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Thesis Abstract

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The process of combining multiple computational intelligence techniques to build a single hybrid model has become increasingly popular. As reported in the literature, the performance indices of these hybrid models are shown to be better than the individual components when used alone. Hybrid models are extremely useful in the field of reservoir characterization in Petroleum Engineering, which requires high-accuracy predictions for efficient exploration, exploitation and management of oil and gas resources.

In this thesis, we have utilized the capabilities of data mining and computational intelligence in the prediction of porosity and permeability, two important petroleum reservoir characteristics, based on the hybridization of Type-2 Fuzzy Logic, Support Vector Machines, and Functional Networks, using eleven well logs. Two hybrid models were built. In both, Functional Networks, using its functional approximation capability with least square fitting algorithm, were used to select the best of the predictor variables for training directly from input data. In the first model, Functional Networks-Fuzzy Logic-Support Vector Machines (FFS), the selected predictor variables were passed to Type-2 Fuzzy Logic System to handle uncertainties and extract inference rules, while Support Vector Machines made the final predictions. In the second model, Functional Networks-Support Vector Machines-Fuzzy Logic (FSF), the selected predictor variables were passed to Support Vector Machines to transform them to a higher dimensional space, and then to Type-2 Fuzzy Logic to handle uncertainties, extract inference rules and make final predictions.

The simulation results showed that the hybrid models perform better than the individual techniques when used alone on the same datasets with their higher correlation coefficients. The hybrid models took less execution time for both training and testing

than the Type-2 Fuzzy Logic, but more time than Functional Networks and Support Vector Machines. This may be the price for having a better and more robust model.

The hybrid models also performed better than a hybridization of just two of the individual components, Type-2 Fuzzy Logic-Support Vector Machines, in terms of both higher correlation coefficients and lower execution times. This is due to the effective role of Functional Networks, as a best-variable selector in the hybrid models.

خلاصـــة الـرســالـــة

الاسم الكامل للطالب : فاتاي أديسينا أنيفوزي

عنــوان الدراسـة : نموذج ذكاءٍ حاسوبي هجينٍ جديدٍ لتمثيلِ مخازن النفط والغاز.

التخـصـص : علوم المعلومات والحاسب

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يتزايد الإقبال على تهجين التقنيات المتعددة للذكاء الحاسوبي في نموذج واحد. وقد أظهرت الدراسات أن مؤشرات أداء النماذج المهجنة بعد الدمج يكون أفضل منها كل على حدى. ومن هنا كان للأنظمة الهجينة الأهمية القصوى في مجال تمثيلِ ودراسة خصائص المخازن النفطية لمهندسي النفط، والتي تتطلب دقة تنبؤ عالية لإستكشاف واستغلال وإدارة موارد النفط والغاز بشكل أمثل.

قمنا في هذه الأطروحة بإستخدام بعض قدرات الذكاء الحاسوبي والتنقيب عن البيانات في التنبؤ بمسامية ونفاذية الصخور، وهما وصفان مهمان للمخازن النفطية. واعتمد العمل فى هذه الأطروحة على النوع الثاني من الأنظمة الضبابة، أجهزة المتجهات الإعتمادية والشبكات الوظيفية في توصيف معلومات أحد عشر بئرا نفطياً. وقد تم تهجين نموذجين في هذه الأطروحة بحيث تقوم الشبكات الوظيفية فى كليهما بإختيار المتغيرات التنبؤية التدريبية، وذلك إعتماداً على ما تتمتع به هذه الشبكات من تقريب للوظيفة والتمثيل الأقرب بحسب مؤشر الخطأ المربع الأدنى.

في نموذج التهجين الأول المعتمد على الشبكات الوظيفية متبوعة بالأنظمة الضبابية فأجهزة المتجهات الإعتمادية (FFS) تم إدخال المتغيرات التنبؤية على النوع الثاني من الأنظمة الضبابة

للتعامل مع الشكوك ولإستخراج قواعد الإستنتاج، بينما قامت أجهزة المتجهات الإعتمادية بعملية التنبؤ النهائية.

أما في نموذج التهجين الثانى المعتمد على الشبكات الوظيفية متبوعة بأجهزة المتجهات الإعتمادية فالأنظمة الضبابية (FSF) فقد تم إدخال المتغيرات التنبؤية على أجهزة المتجهات الإعتمادية لنقلها لدرجة أعلى من الأبعاد، ومن ثم تمرير الناتج للأنظمة الضبابية للتعامل مع الشكوك ولإستخراج قواعد الإستنتاج، بينما قامت أجهزة المتجهات الإعتمادية بعملية التنبؤ النهائية.

وقد أظهرت نتائج المحاكاة على نفس المدخلات أن النماذج الهجينة بمعاملات ارتباطها الأعلى تتصرف بشكل أفضل من أي منها كل على حدى. وقد تتطلبت النماذج الهجينة وقتا أقل للتدريب والتجريب من النماذج الضبابية من النوع الثاني، لكنه أكبر من الذي يتطلبه كل من الشبكات الوظيفية وأجهزة المتجهات الإعتمادية. وقد يكون هذا هو الثمن المقابل للنموذج المهجن الأقوى والأدق.

كما تصرف النظام الهجين الثلاثي بكفاءة تفوق التهجين الضبابي وأجهزة المتجهات الإعتمادية من حيث معاملات إرتباطها الأعلى ووقت التشغيل الأقل، ويرجع هذا للدور الفعال للشبكات الوظيفية كأداة لإختيار أفضل المتغيرات في النموذج الهجين.

Chapter One

Introduction

1.0 Reservoir Characterization

Petroleum reservoir characterization is a process for quantitatively describing various reservoir properties in spatial variability using available field data. Reservoir characterization plays a crucial role in modern reservoir management. It helps to make sound reservoir decisions and improves the asset value of the oil and gas companies. It maximizes integration of multidisciplinary data and knowledge, and it improves the reliability of the reservoir predictions. The ultimate product is a reservoir model with realistic tolerance for imprecision and uncertainty.

Porosity and permeability are the two fundamental reservoir properties which relate to the amount of fluid contained in a reservoir and its ability to flow. These properties have a significant impact on petroleum field operations and reservoir management [1].

1.1 Computational Intelligence

Computational Intelligence (CI) is an offshoot of Artificial Intelligence (AI). It covers all branches of science and engineering that are concerned with the understanding and solving of problems for which effective computational algorithms do not exist. Thus, it overlaps with some areas of Artificial Intelligence and a good part of Pattern Recognition, Image Analysis and Operations Research. It is based on the assumption that thinking is nothing but symbol manipulation. Thus, it holds out the hope that computers will not merely simulate intelligence, but actually achieve it. CI relies on heuristic algorithms such as in Fuzzy Systems, Neural Networks, Support Vector Machines and Evolutionary Computation. In addition, CI also embraces techniques that use Swarm Intelligence, Fractals and Chaos Theory, Artificial Immune Systems, Wavelets, etc. [9].

A good number of studies have been carried out on the use of various Computational Intelligence (CI) schemes to predict the characteristics of oil and gas reservoirs such as depth, temperature, pressure, volume, drive mechanism, structure and seal, diagenesis, well spacing, well-bore integrity, porosity and permeability, using such schemes as Logistic Regression (LR), K-Nearest Neighbor (KNN), Multilayer Perceptrons (MLP), Radial Basis Function (RBF), Bayesian Belief Networks (BBN), Naïve Bayes (NB), Random Forests (RF), Functional Networks (FN), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Probabilistic Networks (PN), Adaptive-Neuro Fuzzy Systems (ANFIS) and Decision Trees (DT) [2-8].

1.2 Hybrid Computational Intelligence

The combination of two or more CI schemes is called Hybrid Computational Intelligence (HCI). This process of combining the results of multiple computational intelligence techniques to produce a single technique is becoming popular. The increased popularity of hybrid intelligent systems in recent times lies in their extensive success in many real-world complex problems [10]. A key prerequisite for the merging of technologies is the existence of a "common denominator" to build upon

[11]. In the case of this work, part of the "common denominator" for the hybridization of Fuzzy Logic, Support Vector Machines and Functional Networks is the inference procedures they deploy and their excellent predictive capabilities.

1.3 Problem Statement

With the identification of the "common denominator" for our hybrid models, we attempt to combine the individual capabilities of Fuzzy Logic, Support Vector Machines and Functional Networks in a hybrid Computational Intelligence Scheme, to predict two characteristics of oil and gas reservoirs, namely Porosity and Permeability, with better performance indices and robustness in their ability to handle uncertainties.

1.4 Motivation

Our motivation for this work can be stated as follows:

- ✓ The quest for higher performance accuracy in the prediction of oil and gas characteristics.
- ✓ The increased popularity of hybrid intelligent systems in recent times.
- ✓ The reported success of these hybrid intelligent systems in many real-world complex problems.
- ✓ The need to complement the weaknesses of one algorithm with the strength of the others and hence to combine the cooperative and competitive characteristics of the individual techniques.

- ✓ Based on the above points, researchers, especially in the areas of Artificial Intelligence, are oriented towards hybrid approaches that combine different theoretical backgrounds and algorithms.
- ✓ It has been theoretically and experimentally justified [12-18] that hybrids produce results which are more accurate than, or competitively equal to, the individual techniques used separately.

The rest of this work is organized as follows. Chapter two addresses a detailed review of literature on Porosity, Permeability, Fuzzy Logic, Support Vector Machines, Functional Networks and Hybrid Systems and their various related works. Chapter three presents the conceptual and experimental design of the hybrid models, a description of how the individual techniques have been combined, the way each block communicates with the other, the role of each technique in the entire system, a full description of data and tools used as well as the criteria used to evaluate the performance of the models. Chapter four gives the results and analysis of the simulation experiments, describing the architecture and the optimized parameters of the models and the results obtained. Chapter five presents the conclusions, detailing the contribution of this work to knowledge, the limitations and a glimpse into areas of future work.

Chapter Two

Literature Survey

2.0 Artificial Intelligence

The application of the capabilities of Artificial Intelligence (AI) has been widely appreciated in Petroleum Engineering in particular, as well as in other fields. This inter-disciplinary endeavor has created a collaborative link between Computer Scientists and Petroleum Engineers in the prediction and simulation of oil and gas reservoir characteristics. Some of the areas of Petroleum Technology in which AI has been used with success include: seismic pattern recognition; porosity and permeability predictions; identification of sandstone lithofacies; drill bit diagnosis; analysis and improvement of oil and gas well production; analysis, prediction and optimization of well performance, bed thickness, proximity to faults, slopes and curvatures of the structure; estimation of irreducible water saturation and oil and gas portfolio management [20, 33, 64].

Mohaghegh [19] described, in detail, how AI can be employed in the field of Petroleum Engineering, with emphasis on Artificial Neural Networks (ANN). He also gave examples of how a carefully designed Neural Network has been used to predict the performance of fracturing jobs with high accuracy in a gas storage field of Ohio county and prediction of the permeability of a highly heterogeneous formation in West Virginia, both in the United States [19].

Other reports of AI techniques as veritable prediction tools for reservoir characterization can be found in [20-23, 25-27, 30, 35].

Besides the prediction of porosity and permeability, another popular area of application of various AI schemes in Petroleum Engineering is in the classification, identification, prediction and extraction of lithofacies from well logs using ANN [23, 25, 26] and Kohonen self-organizing maps [24].

A further important property of oil and gas reservoirs that have benefited immensely from the application of various AI techniques is the Pressure-Volume-Temperature (PVT). This property has been estimated using ANN [27, 28, 29, 31, 34], Radial Basis Function [32] and Support Vector Machines [60].

2.1 Porosity and Permeability

Porosity and permeability measurements are frequently made on plugs extracted from the core of wells drilled for oil and gas exploration. The data are valuable for linking permeability, a quantity not directly measured with well logs, to porosity, a quantity which is routinely determined with well logs. Porosity and permeability data serve as standard indicators of reservoir quality in the oil and gas industry. Each of them will be discussed in the following subsections.

2.1.1 Porosity

Porosity is the percentage of voids and open spaces in a rock or sedimentary deposit. The greater the porosity of a rock, the greater its ability to hold water and other materials, such as oil [36]. It is an important consideration when attempting to evaluate the potential volume of hydrocarbons contained in a reservoir. Sedimentary porosities are a complex function of many factors, including but not limited to, rate of burial, depth of burial, the nature of the carbonate fluids and overlying sediments (which may impede fluid expulsion).

Different types of porosity are Primary, Secondary, Fracture and Vuggy porosity. Primary porosity is the original porosity system in a rock. Secondary porosity is a subsequent porosity system in a rock, often enhancing the overall porosity. This can be as a result of leeching of minerals or the generation of a fracture system. This can replace the primary porosity or co-exist with it. Fracture porosity is a type of porosity that is associated with a fracture system or faulting. This can create secondary porosity in rocks that otherwise would not be reservoirs for hydrocarbons due to their primary porosity being destroyed (for example due to depth of burial) or of a rock type not normally considered a reservoir (for example igneous intrusions or meta-sediments). Vuggy porosity is secondary porosity generated by dissolution of large features (such as macrofossils) in carbonate rocks leaving large holes, vugs, or even caves [38, 39].

2.1.2 Permeability

Although a rock may be very porous, it is not necessarily very permeable. Permeability is the ease with which fluid is transmitted through a rock's pore space. It is a measure of how interconnected the individual pore spaces are in a rock or sediment. It is a key parameter associated with the characterization of any hydrocarbon reservoir. In fact, many Petroleum Engineering problems cannot be solved accurately without having an accurate permeability value [36, 39].

2.1.3 Research on Porosity and Permeability

Attempts have been made to utilize Artificial Neural Networks (ANNs) for identification of the relationship which may exist between well logs and core permeability. However, despite the wide range of applications and flexibility of ANNs, there is still no general framework or procedure through which the appropriate network for a specific task can be designed [40].

Abdelkader et al. [33] used Artificial Neural Network and Fuzzy Logic to characterize naturally fractured reservoirs. Using these tools, they produced 2-D fracture intensity and fracture network maps in a large block of fields. The results showed that the proposed approach is a practical methodology to map the fracture network.

Maqsood and Adwait [41] used Neural Networks to predict permeability from petrographic data while using Fuzzy Logic to screen and rank the predictor variables with respect to the target variable. The Neural Network was used as a multivariate correlative tool because of its ability to learn the non-linear relationships between multiple input and output variables. The result demonstrated the generalizing capability of the Neural Network.

Yuantu et al. [42] introduced a new Neural-Fuzzy technique combined with Genetic Algorithms in the prediction of permeability in petroleum reservoirs. The methodology involved the use of Neural Networks to generate membership functions and to approximate permeability automatically from digitized data (well logs) obtained from oil wells. The trained networks were used as fuzzy rules and hyper-surface membership functions. The results of these rules were then interpolated on the basis of membership grades and the parameters in the defuzzification operators which were optimized by Genetic Algorithms. The results showed that the integrated Neural-Fuzzy-Genetic-Algorithm (INFUGA) gave the smallest error on the unseen data when compared to similar algorithms.

Jong-Se [43] suggested an intelligent technique using Fuzzy Logic and Neural Networks to determine reservoir properties from well logs using Fuzzy Curve Analysis based on Fuzzy Logic for selecting the best related well logs with core porosity and permeability data. Neural Network was then used as a nonlinear regression method to develop transformation between the selected well logs and core measurements. The results showed that the technique estimated the reservoir properties more accurately and reliably than conventional computing methods.

Mohsen et al. [40] proposed a new method for the auto-design of Neural Networks (ANN) based on Genetic Algorithm (GA). Design of the topology and parameters of the Neural Networks as decision variables was done first by trial and error, and then by using Genetic Algorithms, in order to improve the effectiveness of forecasting when ANN was applied to a permeability predicting problem from well logs. Comparison of the prediction performance efficiency of the GA-optimized ANN model with that of the trial-and-error-approach-calibrated ANN model showed that the former outperformed the latter. In other words, GA was found to be a good alternative over the trial-and-error approach to determine the optimal ANN architecture and internal parameters quickly and efficiently. The performance of the nets with respect to the predictions made on the test sets showed that the ANN model incorporating a

GA was able to sufficiently estimate the permeability of the reservoir with a high correlation coefficient.

In order to increase the accuracy and reliability of previously used parametric correlation between different direct measurable parameters such as porosity, depth and permeability, Jamialahmadi and Javadpour [35] utilized a Radial Basis Function Neural Network (RBFNN) for identification of the relationship which may exist between permeability, porosity and depth of a reservoir. The investigation showed that the RBFNN architecture was capable of predicting formation permeability by using laboratory measurement of the cores and the well testing data obtained from the field, while also proving the essentiality of the availability of core data for the training process.

2.2 Overview of Fuzzy Logic

Fuzzy Sets (FS) have been around for nearly 40 years, and they include Type-1 FS (fuzzy) and Type-2 FS (fuzzy fuzzy). Type-2 FS was introduced by Zadeh [44] as an extension of the concept of Type-1 Fuzzy. Type-2 FS have grades of membership that are themselves fuzzy. For each value of primary variable (e.g. pressure and temperature), the membership is a function (not just a point value). This is the secondary Membership Function (MF), whose domain, the primary membership, is in the interval [0,1], and whose range, secondary grades, may also be in [0,1]. Hence, the MF of a Type-2 FS is three-dimensional, and the new third dimension provides new design degrees of freedom for handling uncertainties. Such sets are useful in circumstances where it is difficult to determine the exact MF for a FS, as in modeling a word by a FS (See fig. 1).

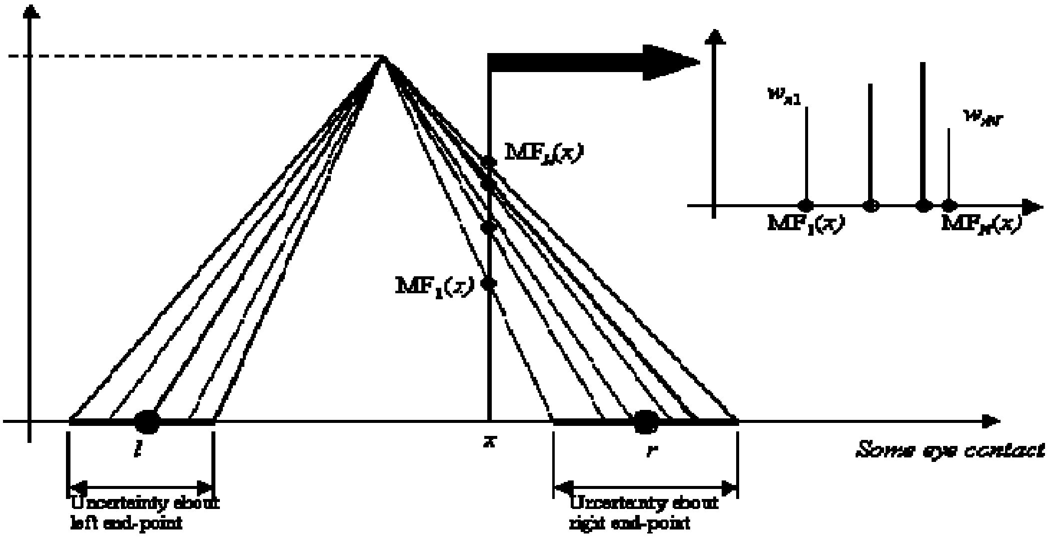

Fig. 1: Triangular MFs with uncertainty intervals base end-points (l and r) (Mendel, 2003)

Fig. 2 shows the structure of a Type-2 Fuzzy Logic System (FLS). It is similar to Type-1 FLS except that the out-processing block contains the defuzzifier. The fuzzifier maps the crisp input into a fuzzy set. This fuzzy set can be a Type-2 set. The distinction between Type-1 and Type-2 is associated with the nature of membership functions, which is not important while forming rules. Hence, the structure of rules remains the same in Type-2. The inference process in Type-2 FLS combines rules and gives a mapping from input Type-2 FS to output Type-2 FS. To do this, one needs to find unions and intersections of Type-2 sets, as well as compositions of Type-2 relations. Extended versions (Zadeh’s extension) can be used to give a Type-1 FS. Since the operation takes one from Type-2 output sets of the FLS to Type-1 sets, this operation can be called “Type Reduction” which is used to produce a “type-reduced sets". To obtain a crisp output from Type-2 FLS, the type-reduced set can be defuzzified. The most natural way of doing this is to find the centroid of the type-reduced set.

So, in order to develop Type-2 FLS, there is the need to be able to do the following:

- Perform the set theoretic operations of union, intersection and complement of Type-2 sets.
- Know the properties (e.g., commutativity, associativity, identity laws) of membership grades of Type-2 sets.
- Deal with Type-2 fuzzy relations and their compositions.
- Perform type reduction and defuzzification to obtain a set-valued or crisp output from the FLS.

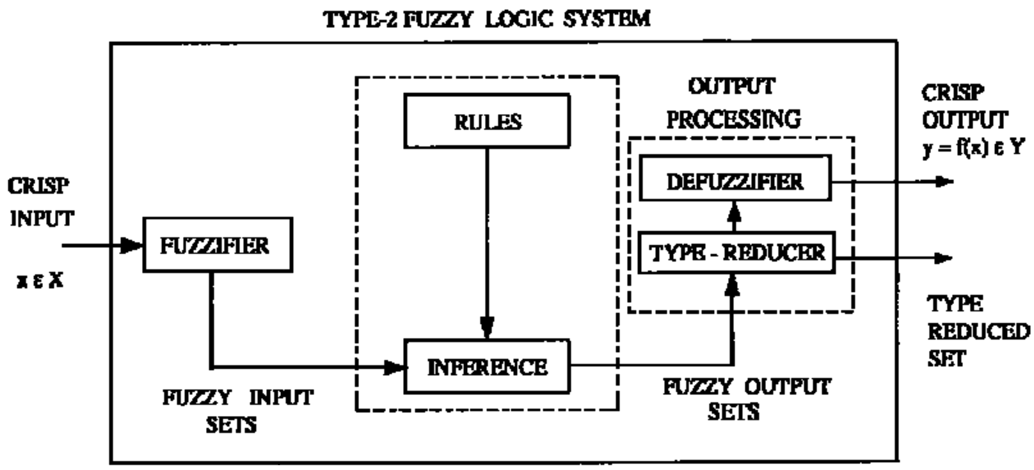

Fig. 2: Structure of a Type-2 FLS (Mendel, 2003)

Definition 1: A type-2 fuzzy set, denoted by Ã, is characterized by a Type-2 membership function $\mu\tilde{A}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0, 1]$, i.e.:

$\tilde{A} = \{((x, u), \mu\tilde{A}(x, u) \mid \forall x \in X, \forall u \in Jx \subseteq [0, 1]\}$ (1)

in which: $0 \leq \mu\tilde{A}(x, u) \leq 1$.

Definition 2: Uncertainty in the primary memberships of a Type-2 Fuzzy Set, Ã, consists of a bounded region that is called the Footprint of Uncertainty (FOU). It is the union of all primary memberships, i.e.:

$$\mathrm{FOU}(\tilde{A}) = \cup_{x \in X} J_x$$

This is shown in fig. 3a and a FOU for Gaussian (primary) MF with uncertain mean is shown in fig 3b.

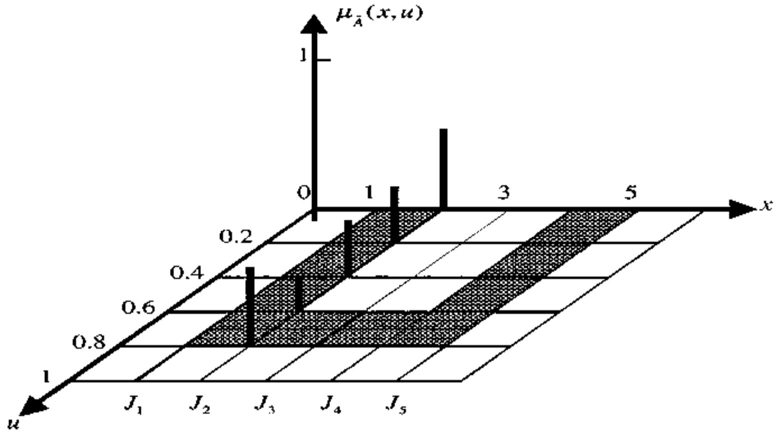

Fig. 3a: Example of Type-2 MF. The shaded area is the FOU (Mendel, 2003).

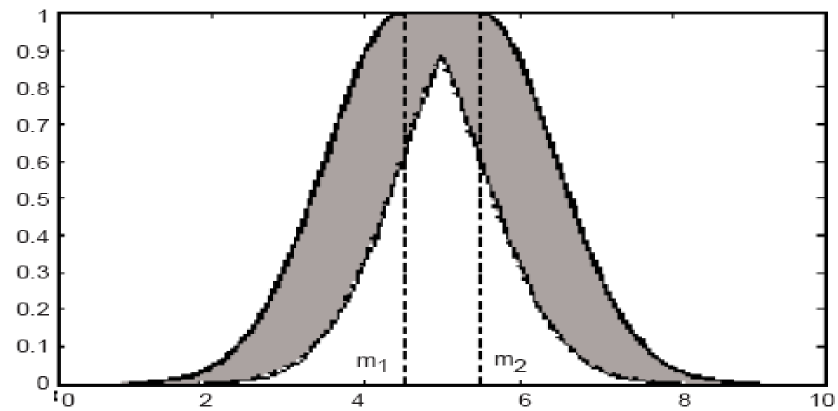

Fig. 3b: Gaussian (primary) MF with uncertain mean (Mendel, 2003).

Type-2 Fuzzy Sets are difficult to understand and use because:

- The three-dimensional nature of Type-2 Fuzzy Sets makes them very difficult to draw.
- There is no simple collection of well-defined terms that let us effectively communicate about Type-2 Fuzzy Sets.
- Derivations of the formulas for the union, intersection, and complement of Type-2 Fuzzy Sets all rely on using Zadeh's extension principle, which in itself is a difficult concept.
- Using Type-2 Fuzzy Sets is computationally more complicated than using Type-1 Fuzzy Sets [45].

Even in the face of these difficulties, Type-2 Fuzzy Sets and FLSs have already been used for many applications including: classification of coded video streams, control of mobile robots, decision making, equalization of nonlinear fading channels, extracting knowledge from questionnaire surveys, forecasting of time series, functional approximation, relational databases, solving fuzzy relation equations, and transport scheduling [46].

Type-2 FLS does not obtain good performance when the quantity of training data is small, but it can perform better than a Type-1 FLS when the quantity of training prototypes is large [45].

2.2.1 Research on Fuzzy Logic

The traditional Fuzzy Logic, now referred to as Type-1 Fuzzy Logic, has featured in a number of research efforts, especially in reservoir characterization. Type-2 Fuzzy

Logic, despite its infancy, has also featured in many recently published articles especially in the areas of finance [47, 50, 56], manufacturing [48], logic control systems [49, 51, 52], information sciences [53, 54], biological sciences [55, 58], mechanics [57] and reservoir properties modeling [33].

One of the earliest references to the application of Fuzzy Logic in the Petroleum Industry was by Fang and Chen [59], who presented a fuzzy modeling for predicting porosity and permeability from the compositional and textural characteristics of sandstones. By comparison with statistical modeling, they found that fuzzy modeling is assumption-free, tolerant of outliers, capable of making both linguistic and numeric predictions based on qualitative knowledge and/or quantitative data, and also desirable for many geological problems characterized by non-numerical knowledge and imprecise information.

Abdelkader et al. [33] used Fuzzy Logic with ANN to characterize naturally fractured reservoirs to reduce the uncertainty by using a Fuzzy Ranking algorithm, which resulted in a more reliable Fracture Index. The results showed that the proposed approach is a feasible and practical methodology to map the fracture network [33].

More studies on Type-2 Fuzzy Logic in oil and gas were carried out mostly in fusion with other techniques, of which ANN and SVM are particularly popular. Some of these have been reported in the previous sections and more will be reported in the hybrid section.

2.3 Overview of Support Vector Machines

Support Vector Machines (SVMs) are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized Linear Classifiers. They can also be considered as a special case of Tikhonov Regularization. SVMs map input vectors to a higher dimensional space where a maximal separating hyperplane is constructed [60]. This is shown in figure 4.

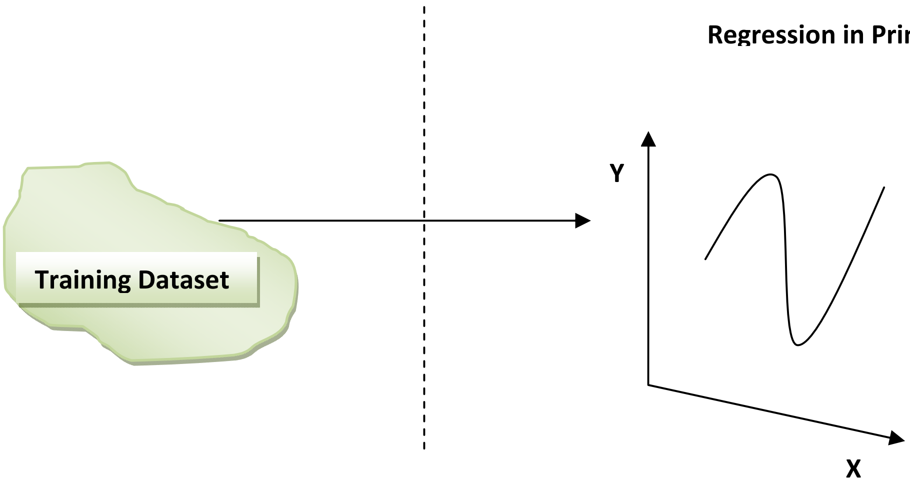

Fig. 4: Mapping input vectors to a higher dimensional space in SVM.

The generalization ability of SVMs is ensured by special properties of the optimal hyperplane that maximizes the distance to training examples in a high dimensional feature space. SVMs were initially introduced for the purpose of classification until 1995 when Vapnik et al., as reported by El-Sebakhy et al. in [60], developed a new ε-sensitive loss function technique that is based on statistical learning theory, and which adheres to the principle of structural risk minimization, seeking to minimize an upper bound of the generalization error. This new technique is called

Support Vector Regression (SVR). It has been shown to exhibit excellent performance.

Further details on SVM can be found in [8, 61, 62, 70].

2.3.1 Research on Support Vector Machines

SVMs have been used extensively in many areas including bioinformatics [63, 72, 74, 77, 79], toxicology [65, 80], physics [66], price forecast in finance [68, 69, 73, 82], multimedia [71], forensics [76], defect prediction in software engineering [78], surface tension prediction in chemistry [81], geotechnical engineering [83] and oil and gas [60, 67] with very promising results.

Among the most recent effort in the application of SVM to reservoir characterization is the report of El-Sebakhy et al. [60] who, while attempting to improve on the weakness of ANN, carried out an assessment of the benefits of SVM in the oil and gas industry by using an SVM modeling approach to predict the PVT properties of crude oil systems. They found that the performance of SVMs is more accurate and reliable and outperforms most of the existing approaches [60].

Taboada et al. [75] created a quality map of a slate deposit, using the results of an investigation based on surface geology and continuous core borehole sampling using different kinds of Support Vector Machines (SVMs): SVM Classification (multi-class one-against-all), Ordinal SVM and SVM Regression. They found that the SVM Regression and Ordinal SVM are perfectly comparable to kriging (a statistical modeling that interpolates data from a known set of sample points to a continuous surface) and possess some additional advantages in terms of interpretability and control of outliers in terms of the support vectors.

Earlier than the above, Jian and Wenfen, while comparing the performances of Group Method of Data Handling, Back Propagation ANN and SVM, concluded that SVM could pay more attention to both the universality and extendibility of a model when the samples are very limited, showing a good prospect of its application [67].

It is observed from the scarcity of SVM works in the area of oil and gas that more work needs to be done in this direction. This thesis is intended to be a useful contribution in this respect.

2.4 Overview of Functional Networks

Functional Networks (FN) is an extension of Neural Networks which consists of different layers of neurons connected by links. Each computing unit or neuron performs a simple calculation: a scalar, typically monotone, function f of a weighted sum of inputs. The function f, associated with the neurons, is fixed and the weights are learned from data using some well-known algorithms such as the least-squares fitting algorithm used in this work.

The main idea of FN consists of allowing the f functions to be learned while suppressing the weights. In addition, the f functions are allowed to be multi-dimensional, though they can be equivalently replaced by functions of single variables. When there are several links, say m links, going from the last layer of neurons to a given output unit, we can write the value of this output unit in several different forms (one per different link). This leads to a system of $m-1$ functional equations, which can be directly written from the topology of the Neural Network. Solving this system leads to a great simplification of the initial functions *f* associated with the neurons.

As shown in fig. 5, a FN consists of a layer of input units which contains the input data (represented by small black circles with its corresponding name), a layer of output units which contains the output data (also represented by small black circles with its corresponding name), and one or several layers of neurons or computing units which evaluates a set of input values coming from the previous layer and gives a set of output values to the next layer of neurons or output units. The computing units are connected to each other, in the sense that output from one unit can serve as part of input to another neuron or to the units in the output layer. Once the input values are given, the output is determined by the neuron type, which can be defined by a function.

For example, assume that we have a neuron with s inputs: $(x_1, \ldots, x_s)$ and k outputs: $(y_1, \ldots, y_k)$, then we assume that there exist k functions F_j; $j = 1, \ldots, k$, such that $y_j = F_j(x_1, \ldots, x_s)$; $j = 1, \ldots, k$.

FN also consists of a set of directed links that connect the input layer to the first layer of neurons, neurons of one layer to neurons of the next layer, and the last layer of neurons to the output units. Connections are represented by arrows, indicating the direction of information flow [84].

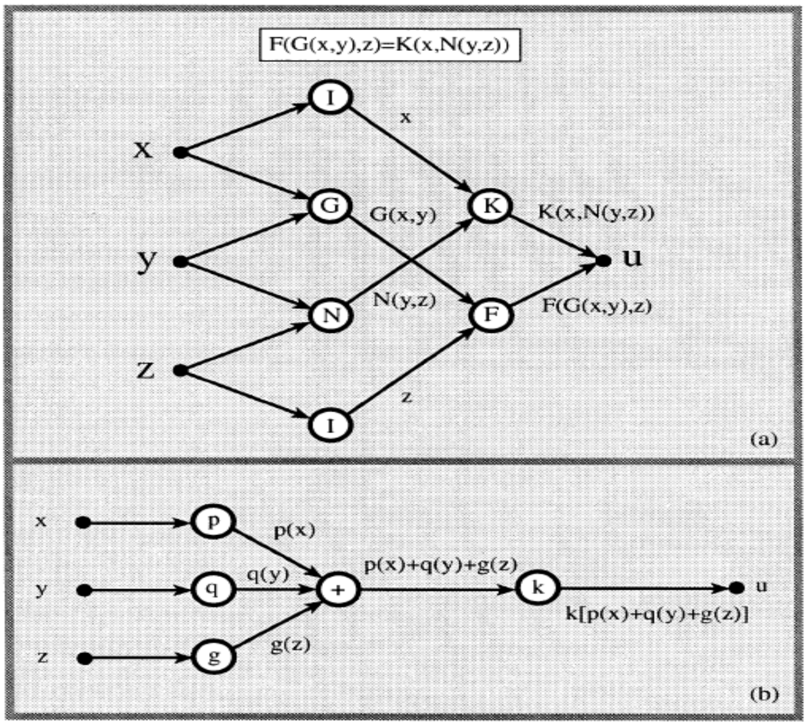

Fig. 5: Illustration of the Generalized Associativity Functional Network.

(a) Initial network (b) Equivalent simplified network (Sebakhy, 2006).

Further details on FN can be found in [8, 61, 85, 86, 87].

2.4.1 Research on Functional Networks

Like the other AI techniques described in previous sections, FN have also featured in a number of studies such as El-Sebakhy [85] who demonstrated FN's reliability, flexibility, stability, and high quality performance by applying it to Thalassemias Data for the classification of genetic defects using stratified sampling and cross-validation techniques to make sure that the same proportion from each group as in the original data is obtained [85].

Castillo et al. [87] gave a comprehensive demonstration of the application of FN in Statistics and Engineering. It was, however, observed in the literature that not much has been done with FN in the field of reservoir characterization. Again, this thesis is intended to be a useful contribution.

2.5 Overview of Hybrids

An approach resulting from the combination of two or more approaches is called a Hybrid. It has also been defined as an approach that combines different theoretical backgrounds and algorithms such as data mining and soft computing methodologies. A key prerequisite for the merging of technologies is the existence of a "common denominator" to build upon [11].

2.5.1 Research on Hybrids

Most hybrids found in the literature usually contain Neural Networks fused with one other technique [43, 89, 90, 91, 92, 93, 94, 95, 96]. This is possibly due to the age of Neural Networks and their wide acceptance and use in the world of computational intelligence [97, 98].

Other hybrid systems include:

- Support Vector Machines with Genetic Fuzzy feature transformation [99],
- Support Vector Learning with Fuzzy Logic [100, 102, 103, 104, 107],
- Decision Trees (DT) and Support Vector Machines (SVM) [101],
- Fuzzy Logic and Extreme Learning Machines [105, 108],
- Neural Network and Genetic Algorithm [106],

- Neural Network with Hidden Markov Model [92],
- Neural Method with Radial Basis Functions [95], and
- Type-2 Fuzzy with Hidden Markov Models [108],

These techniques featured in such areas as biometrics [93, 99, 100, 108], finance [104], multimedia processing [102], networks security [101], control systems [89, 90] and reservoir characterization [43, 91, 92, 94, 95, 96, 99, 103, 105, 106].

A fuzzy Linear Programming Support Vector Machines (LP-SVMs) that resolved unclassifiable regions for multiclass problems by defining membership functions in the directions orthogonal to the decision functions, and by extension defining a membership function for each class, was proposed by Abe [103]. The work demonstrated the superiority of the Fuzzy LP-SVMs hybrid over the conventional SVMs.

Jong-Se [43] suggested an intelligent technique using Fuzzy Logic and Neural Networks to determine reservoir properties from well logs. He used Fuzzy Logic to select the best related well logs with core porosity and permeability data, and Neural Networks, to develop transformations between the selected well logs and core measurements. The results showed that the technique gave a more accurate and reliable reservoir properties estimation compared to conventional computing methods.

Deyi et al. [96] developed a methodology that provides a hybrid Genetic Programming and Fuzzy/Neural Network inference system which utilizes lithologic and permeability facies as indicators to estimate the permeability of reservoirs using Genetic Programming. To predict permeability facies within lithology type, a Fuzzy/Neural Network inference algorithm was used to form a Fuzzy Logic relationship for each permeability facies and lithology. When compared with contemporary estimation approaches, the hybrid yielded more consistent and robust estimated results.

Ferraz and Garcia [91] presented a hybrid tool that combined Neural Networks and Fuzzy Logic to improve human intuition when analyzing the potential of oil fields through the determination of rock formations of each layer of a given reservoir. The result obtained for the Neuro-Fuzzy hybrid was comparable to that of Neural Network used separately.

Chikhi and Batouche [95] combined a probabilistic neural method with Radial Basis Functions in order to construct the lithofacies of the wells in the Sahara by using a probabilistic formalism to enhance the classification process initiated by a self-organized map procedure. This was followed by a similar hybridization effort by Salim [92] who combined the respective capabilities of Neural Networks (NNs) and Hidden Markov Models (HMMs) to produce a new effective and a more reliable hybrid model in order to obtain the lithology identification of wells in the Sahara region. Comparisons were established to show that the results obtained by the NN-HMM hybrid system are close to those obtained by the fuzzy Adaptive Resonance Theory (ART) approach applied to the same borehole with the same well logs.

Ho and Ehara [94] suggested a method to determine reservoir properties from a well log by using a fusion of Fuzzy Logic and Neural Networks. They used Fuzzy Logic for noise rejection of training data for the Neural Networks to perform a nonlinear transformation for the prediction of porosity and permeability with higher accuracy. The results of the approach showed that this technique estimated the reservoir properties more accurately and reliably than conventional computing methods.

Chen et al. [88] researched the hybridization of Support Vector Machines (SVMs) and Interval Type-2 Fuzzy Logic System (FLS). To better handle uncertainties existing in real classification data and in the membership functions (MFs) in the traditional Type-1 Fuzzy Logic System (FLS), an Interval Type-2 Fuzzy Set was applied to construct a Type-2 SVM fusion FLS. This was achieved by using Type-2 fusion architecture to obtain the classification results from the individual SVM classifiers and then to generate the combined classification decisions as the output.

In line with the good performance of hybrid techniques, coupled with the promising potentials of the individual techniques in the development of hybrid models, we have obtained good results that are comparable to those reported in the literature while modeling two characteristics of reservoirs (porosity and permeability) with these hybrid schemes.

Chapter Three

Design of the Hybrid Models

3.0 Methodology

The methodology in this work is based on the standard Computational Intelligence approach to hybridization of AI technique using Fuzzy Logic (FL), Support Vector Machines (SVM) and Functional Networks (FN). The hybrids were designed in order to benefit immensely from the strength of the individual techniques and to complement the weaknesses of each technique with the advantages of the others by combining the cooperative and competitive characteristics of the individual techniques.

Two hybrid models have been built. In both models, FN was used to select the best variables for training directly from the input data by using its functional approximation capability with least-square fitting algorithm. In the first hybrid model, code-named FFS, the selected best variables from the Functional Networks block were passed to the Type-2 Fuzzy Logic block to handle uncertainties and extract inference rules, while the Support Vector Machines block made the final predictions. In the second model, code-named FSF, the selected best variables were passed to Support Vector Machines for transformation to higher dimensional space, and then to Type-2 Fuzzy Logic to handle uncertainties, extract inference rules and make final predictions. These are explained in more detail in sections 3.4.1 and 3.4.2 respectively.

In order to fully comprehend how the two hybrids work, the following sections discuss the strengths and weaknesses of the individual techniques.

3.1 Strengths and Weaknesses of Fuzzy Logic

Type-2 Fuzzy Logic System has been used in this work. The choice of this system lies in its ability to determine an exact membership function for a fuzzy set. Hence it is useful for handling uncertainties [44]. It is also effective in the process of extracting rules, to be used for inferencing, directly from the input data.

However, its disadvantage lies in its complexity of implementation, requiring too much time to tune the parameters used for inferencing during the process of training and testing, compared to other techniques. Also, Type-2 Fuzzy Logic does not obtain good performance when the quantity of the training data is small, but it performs better when the quantity of the training prototypes is large [45].

3.2 Strengths and Weaknesses of Support Vector Machines

Although the use of SVMs in applications has only recently begun, application developers have already reported state-of-the-art performances in a variety of applications in pattern recognition, regression estimation, and time-series prediction [61]. Its strengths lie mainly in its relative ease of training. It has no local optima, unlike in Neural Networks. It scales relatively well to high dimensional data. It has the ability to explicitly control the tradeoff between complexity and error, and it is able to handle non-traditional data such as trees for input to the system, instead of feature vectors. SVM is also known to have the capability of using a small training dataset. However, it is weak in the sense that it needs a “good” kernel function [62].

3.3 Strengths of Functional Networks

Functional Networks (FNs) were introduced as a generalization of Neural Networks. They deal with general functional models instead of sigmoidal-like ones. In FN, the functions associated with the neurons are not fixed but are learnt directly from the available data. Hence, there is no need to include weights associated with links. FN has the capability of dealing with functional constraints that are determined by the functional properties of the network model.

The learning process of FN consists of obtaining the neural functions based on a set of training data. Usually, the learning process is based on minimizing the sum of squared errors between the input and the target output. This is done by learning the neural functions by suggesting an approximation to each of the functions and selecting the best among them [61].

The description of the techniques used in this work in terms of strengths and weaknesses is summarized in table 1.

3.4 Conceptual Design of the Hybrid Models

To achieve our aim, two different but similar models of the hybrid were built: FN-Fuzzy Logic-SVM (FFS) and FN-SVM-Fuzzy Logic (FSF). FN was used as the base for each of the models. This is due to its functional approximation capability to select the best variables for the system directly from the training data.

The following subsections describe the conceptual framework design of the two hybrid models and the optimized parameters of each of the techniques before they were used in the hybrids.

Technique	Strength	Weakness
Type-2 FLS	- Ability to determine exact membership functions for a fuzzy set. - Ability to handle uncertainties. - Ability to extract rules directly from input data.	- Complexity of implementation. - Too much time spent in tuning the parameters used for inferencing during the training and testing processes. - Does not obtain good performance when the quantity of training data is small.
SVM	- Ease of training. - No local optima, unlike in Neural Networks. - It scales relatively well to high dimensional data. - Ability to explicitly control the tradeoff between complexity and error. - It is also known to have the capability of using small training dataset.	- It is weak in the sense that it needs a "good" kernel function.
FN	- There is no need to include weights associated with links. - Functional approximation. - Ability to select the best among functions by minimizing the sum of square errors.	

Table 1: Summary of the Strengths and Weaknesses of Type-2 FLS, SVM and FN.

3.4.1 FN-Fuzzy Logic-SVM (FFS)

This model is composed of three major blocks containing respectively Functional Networks (FN), Type-2 Fuzzy Logic (Fuzzy Logic) and Support Vector Machines (SVM). The FN block, using its least-squares fitting algorithm, is used to select the best variables from the input data. The dimensionality of the input data can be ignored. This is automatically handled by the FN block that plays the role of a best-variable selector in the model. The best variables are extracted from the input data and then divided into training and test sets using the Stratified Sampling approach, to be fully described in section 4.0. The training set is passed to the Fuzzy Logic block where uncertainties are removed, if any exists. Already, Type-2 Fuzzy Logic System has been shown in several works such as in [43, 44, 47, 50, 52 - 55] to have the ability to remove uncertainties using its extension to a third dimension. Making an attempt to re-confirm this already established fact is not within the scope of this work. The training data, with uncertainties removed, is then used to train the SVM block in readiness for prediction with the test data. Finally, the test data is passed to the trained SVM block to perform the regression task.

The role performed by the Fuzzy Logic block in this model is to ensure that in case an input data containing uncertainties is used, such uncertainties would have been removed before the data is passed to the SVM block for training. In this way, only "clean" data is allowed to enter the SVM block which performs the prediction task after the training process. This is an attempt to complement the performance of the hybrid with the ability of Type-2 Fuzzy Logic to handle uncertainties.

Figure 6 shows the conceptual design framework of this model.

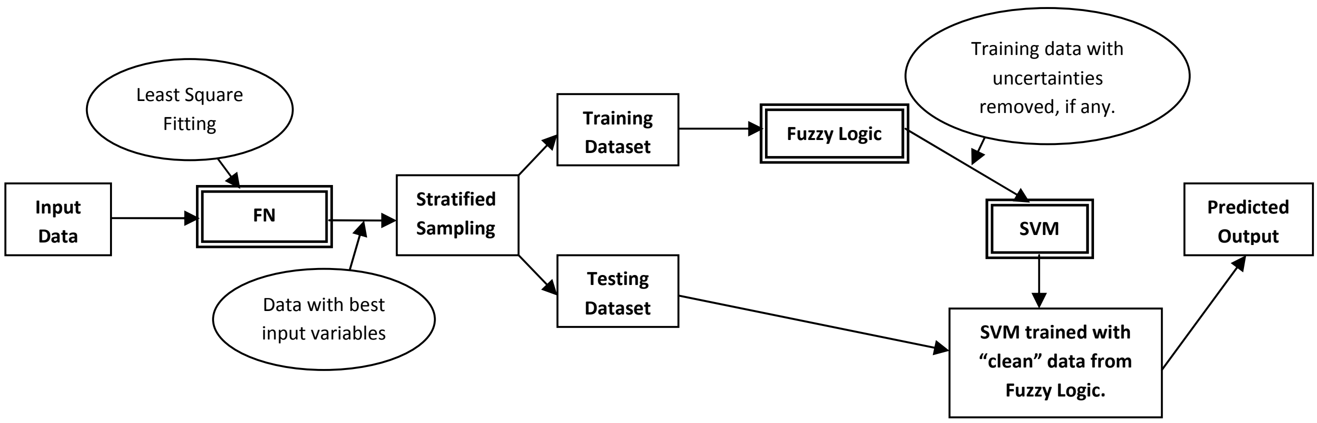

Figure 6: Conceptual design framework of FFS hybrid model.

3.4.2 FN - SVM - Fuzzy Logic (FSF)

Similar to FFS described in the previous section, this model is composed of three major blocks containing respectively Functional Networks (FN), Support Vector Machines (SVM) and Type-2 Fuzzy Logic (Fuzzy Logic). The architecture of this model is similar to the one described in the previous section. The only difference is that the Type-2 Fuzzy Logic and SVM blocks in the FFS are transposed to obtain a new architecture.

In this model, the best variables extracted by the FN block, by using its least-squares fitting algorithm, are also divided into training and test sets using the Stratified Sampling approach mentioned in the previous section. The training dataset is passed to the SVM block. The process of training in SVM involves the transformation of the input data to a higher dimensional space. The SVM block transforms the training set to a higher dimensional space and passes it to the Type-2 Fuzzy Logic block for training. Training in Type-2 Fuzzy Logic System involves fuzzification and transformation to a higher dimension (the third dimension) where uncertainties are easily handled and inference rules are extracted from the input data. The final predictions are made by passing the test data through the trained Fuzzy Logic block.

The role performed by the SVM block in this model is to ensure that, in case the volume of the training data is small, the hybrid will still be able to cope. This is an attempt to complement the performance of the hybrid with the ability of SVM to handle small training and test data sets.

Figure 7 shows the conceptual design framework of this model.

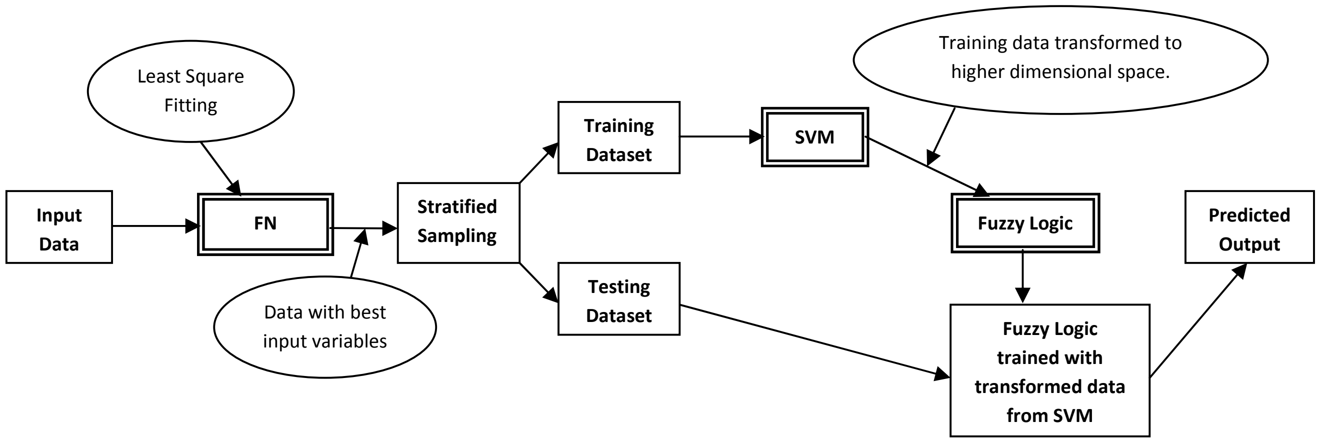

Figure 7: Conceptual design framework of FSF hybrid model.

3.5 Data

Two sets of well logs were used for the design, implementation and validation of this work: a set of well logs obtained from a drilling site containing three wells for porosity in the Northern Marion Platform in North America (site 1) [109] and another set of well logs from a drilling site containing three wells for porosity and five wells for permeability in the Middle East (site 2). The datasets from site 1 have six predictor variables for Porosity, while the datasets from site 2 have eight predictor variables for permeability. These are shown in tables 2 and 3.

The hybrid models were implemented using mainly MATLAB codes and MATLAB toolboxes for SVM, FN and Type-2 Fuzzy Logic.

Tables 4 - 6 display the descriptive statistics for the three datasets of wells for porosity obtained from site 1. Tables 7 – 9 and tables 10 - 14 display respectively the descriptive statistics of three datasets of wells for porosity and five datasets of those wells for permeability obtained from site 2.

Predictor Variables for Site 1 Porosity	
1	Core
2	Top Interval
3	Grain Density
4	Grain Volume
5	Length
6	Diameter

Table 2: Predictor Variables for Site 1 well log for Porosity.

Predictor Variables for Site 2 Permeability		Full Meaning
1	GR	Gamma Ray Log
2	PHIE	Porosity Log
3	RHOB	Density Log
4	SWT	Water Saturation
5	RT	Deep Resistivity
6	MSFL	Microspherically Focused Log
7	NPHI	Neutron Porosity Log
8	CALI	Caliper Log

Table 3: Predictor Variables for Site 2 well log for Permeability.

	Core	Top Interval	Grain Density	Grain Volume	Length	Diameter
Std	**21.09**	**44.138**	**0.0412**	**1.929**	**0.23**	**0.03**
Min	**1**	**1**	**2.6**	**0**	**1.66**	**2.15**
Max	**67**	**146**	**2.85**	**12.76**	**3.01**	**2.56**
Mean	**22**	**62.9**	**2.77**	**9.409**	**2.38**	**2.51**
Median	**13**	**56**	**2.78**	**9.715**	**2.39**	**2.52**
Mode	**1**	**11**	**2.81**	**11.15**	**2.39**	**2.53**
Var	**446**	**1948**	**0.0017**	**3.722**	**0.05**	**0.00109**

Tables 4: Descriptive statistics of Site 1, Well 1 for Porosity

	Core	Top Interval	Grain Density	Grain Volume	Length	Diameter
Std	**21.29**	**39.45**	**0.021**	**2.81**	**12.70**	**10.15**
Min	**1**	**0**	**2.67**	**4.62**	**1.49**	**0.53**
Max	**67**	**145**	**2.89**	**18.19**	**54.48**	**25.38**
Mean	**28.35**	**59.99**	**2.74**	**11.61**	**10.59**	**8.79**
Median	**24**	**55**	**2.74**	**11.56**	**3.33**	**2.53**
Mode	**1**	**27**	**2.74**	**11.56**	**2.74**	**2.53**
Var	**453.30**	**1556.37**	**0.00045**	**7.926**	**161.38**	**103.03**

Tables 5: Descriptive statistics of Site 1, Well 2 for Porosity

	Top Interval	Grain Volume	Length	Diameter
Std	**38.27**	**24.80**	**1.52**	**0.78**
Min	**2**	**8.97**	**5.77**	**5.64**
Max	**130**	**111.46**	**10.6**	**8**
Mean	**66.09**	**44.12**	**7.68**	**6.02**
Median	**61**	**38.7**	**7.11**	**5.72**
Mode	**30**			**5.7**
Var	**1464.63**	**614.83**	**2.32**	**0.62**

Tables 6: Descriptive statistics of Site 1, Well 3 for Porosity

	DT	GR	PHIE	RHOB	SWT
Std	**5.12**	**6.82**	**6.36**	**0.09**	**0.39**
Min	**44.50**	**18.911**	**0**	**2.68**	**0.032**
Max	**65.25**	**58.83**	**25.72**	**3.06**	**1**
Mean	**51.95**	**30.11**	**6.43**	**2.82**	**0.62**
Median	**49.76**	**28.45**	**4.13**	**2.81**	**0.77**
Mode	**48.62**	**30.86**	**1.77**	**2.71**	**1**
Var	**26.25**	**46.52**	**40.47**	**0.008**	**0.15**

Tables 7: Descriptive statistics of Site 2, Well 1 for Porosity

	DT	GR	PHIE	RHOB	SWT
Std	**5.83**	**6.27**	**7.30**	**0.088**	**0.33**
Min	**47.01**	**25.07**	**0.038**	**2.59**	**0.069**
Max	**70.51**	**60.76**	**27.94**	**2.98**	**1**
Mean	**5.12**	**6.82**	**6.36**	**0.09**	**0.39**
Median	**53.08**	**34.99**	**5.33**	**2.78**	**0.77**
Mode					**1**
Var	**34.03**	**39.31**	**53.27**	**0.0078**	**0.11**

Tables 8: Descriptive statistics of Site 2, Well 2 for Porosity

	DT	GR	PHIE	RHOB	SWT
Std	**5.26**	**7.36**	**4.55**	**0.040**	**0.26**
Min	**47.23**	**20.96**	**0**	**2.68**	**0.18**
Max	**68.70**	**58.83**	**20.04**	**2.86**	**1**
Mean	**51.49**	**33.61**	**2.63**	**2.75**	**0.88**
Median	**49.23**	**32.63**	**0.75**	**2.75**	**1**
Mode			**0**		**1**
Var	**27.67**	**54.15**	**20.68**	**0.0015**	**0.067**

Tables 9: Descriptive statistics of Site 2, Well 10 for Porosity

	X2	X3	X4	X5	X6	X7	X8	X9
Std	**0.46**	**0.05**	**0.07**	**0.14**	**0.18**	**0.10**	**0.030**	**0.03**
Min	**0.54**	**0.030**	**0.03**	**2.18**	**0.04**	**8.15**	**0.0001**	**0.003**
Max	**2.44**	**0.26**	**0.29**	**2.67**	**1**	**8.49**	**0.11**	**0.13**
Mean	**1.18**	**0.14**	**0.15**	**2.44**	**0.17**	**8.41**	**0.049**	**0.06**
Median	**1.18**	**0.13**	**0.14**	**2.47**	**0.11**	**8.46**	**0.055**	**0.06**
Mode				**2.21**	**0.04**	**8.47**	**0.0001**	
Var	**0.21**	**0.002**	**0.004**	**0.02**	**0.03**	**0.01**	**0.001**	**0.001**

Tables 10: Descriptive statistics of Site 2, Well 1 for Permeability

	X2	X3	X4	X5	X6	X7	X8	X9
Std	**0.30**	**8.92**	**0.06**	**0.07**	**0.12**	**0.26**	**0.06**	**0.19**
Min	**0.45**	**49.28**	**0.02**	**0.01**	**2.25**	**0.04**	**6.00**	**0.00**
Max	**1.85**	**81.13**	**0.24**	**0.26**	**2.70**	**1.00**	**6.24**	**0.74**
Mean	**1.25**	**64.81**	**0.14**	**0.14**	**2.47**	**0.50**	**6.08**	**0.21**
Median	**1.27**	**64.56**	**0.14**	**0.14**	**2.48**	**0.49**	**6.05**	**0.12**
Mode						**1.00**	**6.08**	
Var	**0.09**	**79.48**	**0.003**	**0.004**	**0.02**	**0.07**	**0.004**	**0.04**

Tables 11: Descriptive statistics of Site 2, Well 2 for Permeability

	X2	X3	X4	X5	X6	X7	X8	X9
Std	0.47	9.54	0.06	0.07	0.13	0.31	0.02	0.09
Min	1.48	49.98	0.01	0.00	2.21	0.04	5.90	0.01
Max	4.03	87.31	0.27	0.28	2.90	1.00	6.00	0.63
Mean	2.19	63.79	0.12	0.12	2.50	0.43	5.97	0.09
Median	2.09	60.78	0.11	0.11	2.53	0.39	5.98	0.06
Mode						1.00	6.00	
Var	0.22	90.95	0.004	0.005	0.02	0.10	0.0006	0.007

Tables 12: Descriptive statistics of Site 2, Well 4 for Permeability

	X2	X3	X4	X5	X6	X7	X8	X9
Std	0.5	8.2	0.1	0.1	0.1	0.3	0.2	0.0
Min	1.1	51.2	0.0	0.0	2.2	0.0	6.2	0.0
Max	4.0	82.7	0.3	0.3	2.7	1.0	7.1	0.2
Mean	2.0	65.1	0.1	0.1	2.5	0.3	6.3	0.1
Median	1.8	63.7	0.1	0.1	2.5	0.1	6.2	0.1
Mode				0.3	2.2	1.0	6.2	
Var	0.2	68.0	0.003	0.005	0.02	0.067	0.025	0.001

Tables 13: Descriptive statistics of Site 2, Well 6 for Permeability

	X2	X3	X4	X5	X6	X7	X8	X9
Std	9.6	0.1	0.1	0.2	0.4	0.0	0.2	0.0
Min	46.8	0.0	0.0	2.2	0.0	6.4	0.0	0.0
Max	79.8	0.4	0.3	2.7	1.0	6.5	0.8	0.2
Mean	62.8	0.1	0.1	2.5	0.6	6.4	0.2	0.0
Median	61.8	0.1	0.1	2.5	0.7	6.4	0.1	0.0
Mode					1.0			
Var	92.7	0.008	0.01	0.007	0.024	0.14	0.0004	0.05

Tables 14: Descriptive statistics of Site 2, Well 7 for Permeability

3.6 Tools

The two hybrid models were implemented using mainly MATLAB codes, the MATLAB toolboxes for SVM, FN and Fuzzy Logic and the Netlab toolbox, obtained as freeware from [110].

3.7 Criteria for Performance Evaluation

From various criteria for performance evaluation used in the literature, we considered the following commonly used ones to evaluate the performance of the results of this study, based on their relevance. They are explained as follows:

3.7.1 Correlation Coefficient

The correlation coefficient measures the statistical correlation between the predicted and actual values. This method is unique, in the sense that it does not change with a scale in values. A higher number means a better model, with a "1" meaning perfect statistical correlation and a "0" meaning there is no correlation at all.

This performance measure is only used for numerical input and output.

The formula is:

$$\frac{\sum(x-x')(y-y')}{\sqrt{\sum(x-x')^2\sum(y-y')^2}}$$

where x and y are the actual and predicted values while x' and y' are the mean of the actual and predicted values.

3.7.2 Root Mean-Squared Error

The mean-squared error is one of the most commonly used measures of success for numeric prediction. This value is computed by taking the average of the squared differences between each predicted value x_n and its corresponding actual value y_n. The root mean-squared error is simply the square root of the mean squared error. The root mean-squared error gives the error value the same dimensionality as the actual and predicted values.

The formula is:

$$\sqrt{\frac{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ldots + (x_n - y_n)^2}{n}}$$

where n is the size of data.

3.7.3 Execution Time

This is simply the total time taken for a technique to run from the beginning to its end. It is computed as follows:

$$T_2 - T_1$$

where T_2 is the CPU time at the end of the run and T_1 is the CPU time at the beginning of the run.

Chapter Four

Simulation Results and Analysis

4.0 Implementation and Validation

We implemented and validated the individual techniques as well as their hybrids in the prediction of Porosity and Permeability using the available data described in the previous chapter.

The available data for each of the wells was divided into training and test data using the stratified sampling technique. This approach ensures most fairness in dividing the data without any bias or preference. As popularly used in the literature, 70% of the entire data goes for training and the remaining 30% goes for testing. To further ensure fairness and integrity of the results obtained, several iterations were made and the average of the runs was obtained.

Table 15 and 16 show the well logs with their sizes and divisions into training and test sets for Porosity and Permeability respectively.

	Site 1			Site 2		
Wells	**1**	**2**	**3**	**1**	**2**	**3**
Data Size	415	285	23	293	183	97
Training (70%)	291	200	16	205	128	68
Testing (30%)	124	85	7	88	55	29

Table 15: Division of datasets into training and testing for Porosity

	Site 2				
Wells	**1**	**2**	**3**	**4**	**5**
Data Size	355	477	431	387	40
Training (70%)	247	334	302	271	28
Testing (30%)	106	143	129	116	12

Table 16: Division of datasets into training and testing for Permeability

4.1 Configuration and Optimal Tuning Parameters

The configuration and the optimal parameters of each of the techniques that were used in the Hybrid models are described in the following subsections:

4.1.1 Functional Networks

The Least Squares Fitting algorithm was used for the implementation of the Associativity Functional Networks. This algorithm has the ability to learn itself and to use the input data directly, by minimizing the sum of squared errors, in order to obtain the parameters, namely the number of neurons and the type of kernel functions, needed for training.

4.1.1.1 Simplifying the Initial Functional Network

Since altogether, eleven datasets were used for the simulation in this work, it would be cumbersome to state the details of each of the initial Functional Networks and how they have been simplified. In a typical case, where the value of Porosity or Permeability of a well is determined by three properties (namely: x, y and z) so that d = D(x, y, z).

The responses can be represented as:

(1) We measure x and y, then z: D(x, y, z) = F(P(x, y), z).

(2) We measure y and z, then x: D(x, y, z) = G(Q(y, z), x).

(3) We measure x and z, then y: D(x, y, z) = H(R(x, z), y).

These responses can be represented in the following networks:

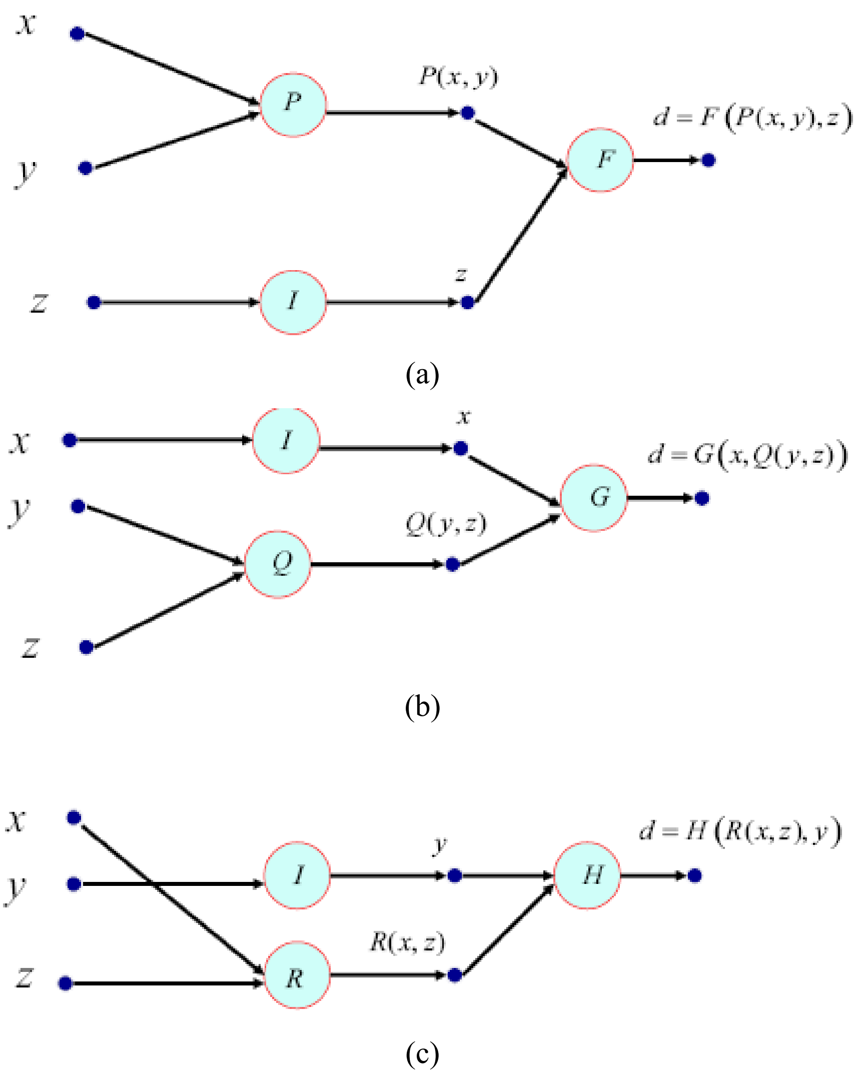

Fig. 8(a) Initial Functional Network, (b) and (c) its equivalent.

Combining the three cases together, we obtain:

$D = F(P(x, y), z) = G(Q(y, z), x) = H(R(x, z), y)$

This equivalence is also represented as:

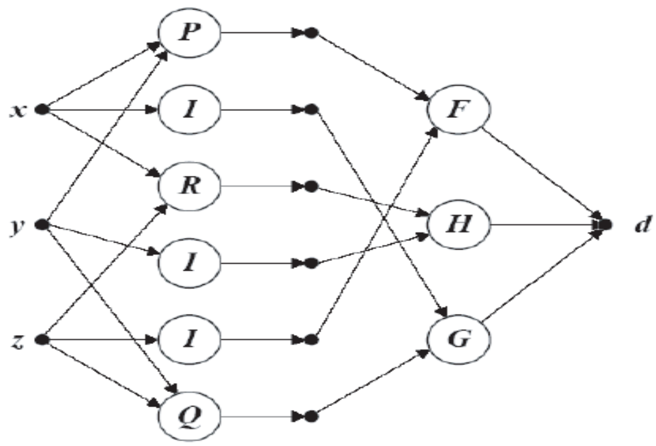

Fig. 9: Initial topology of the Functional Network corresponding to the combined functional equations

This initial network is simplified using the general solution of functional equations as:

$F(x, y) = k[f(x) + r(y)]$, $P(x, y) = f^{-1}[p(x) + q(y)]$,

$G(x, y) = k[n(x) + p(y)]$, $Q(x, y) = n^{-1}[q(x) + r(y)]$,

$H(x, y) = k[m(x) + q(y)]$, $R(x, y) = m^{-1}[p(x) + r(y)]$,

where f, r, k, m, p, q, n are arbitrary continuous and strictly monotonic functions. Substituting the above equations into the previous one, we obtain:

$d = D(x, y, z) = k[p(x) + q(y) + r(z)]$.

which is equivalent to the simplified version of the initial network as:

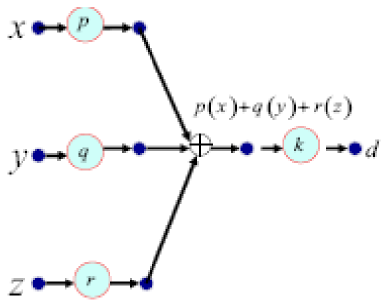

Fig. 10: Simplified Network

Generally, all solutions of the functional equation of the form:

$$\sum_{i=1}^{n} f_i(x) g_i(y) = 0$$

can be written as:

$$F(x) = A\varphi(x),\ g(x) = B\psi(x).$$

where A and B are constant matrices of dimensions n x r and n x (n-r) respectively, with $A^TB = 0$.

0 is a r x (n-r) matrix.

$\varphi(x) = \{\varphi_1(x),...,\varphi_r(x)$ and $\psi(x) = \{\psi_{r+1}(y),...,\psi_n(y)\}$

are two arbitrary systems of mutually linearly independent functions and r is an integer between 0 and n.

4.1.1.2 Model Selection

In order to learn the Functional Network, there was the need to do a model selection to choose the best Functional Network model using the Minimum Description Length (MDL) principle. This measure allows comparisons not only of the quality of different approximations, but also of different Functional Network models. It is also used to compare models with different parameters, because it has a penalty term for overfitting. Moreover, it is distribution-independent. This makes it a convenient method for solving the model selection problem. Accordingly, the best Functional Network model for a given problem corresponds to the one with the smallest description length value. This was calculated using the Backward-Forward method.

The backward process starts with the complete model with all parameters, and it sequentially removes the one leading to the smallest value of the MDL measure, repeating the process until there is no further improvement in the measure. Next, the forward process is applied, but starting from the final model of the backward process, and it sequentially adds the variable that leads to the smallest value of MDL measure. This process is repeated until there is no further improvement in MDL measure is obtained either by removing or adding a single variable.

The significant role of Functional Networks in this work was remarkably demonstrated by the reduction in the dimensionality of the datasets for porosity to 2, 3, 4 and 5, according to their relevance in the system. Similarly, the dimensionality of the datasets for permeability was reduced to 2, 3, 4 and 6 variables.

4.1.2 Support Vector Machines

For the same reason that eleven datasets were used to design and validate this work, the general behavior of SVM will be described.

Given a set of data points, $G = \{(x_i, d_i)\}_i^n$ where x_i is the input vector, d_i is the desired target value and n is the total number of data points, SVMs approximate the function with three distinct characteristics:

- ✓ Estimating the regression in a set of linear functions.
- ✓ Defining the regression estimation as the problem of risk minimization with respect to the ε-insensitive loss function.
- ✓ Minimizing the risk by using the Structural Risk Minimization (SRM) principle whereby elements of the structure are defined by the inequality ||w||2 ≤ constant.

The linear function is formulated in the high dimensional feature space, with this form of function:

$$y = f(x) = w\,\Phi(x) + b$$

where $\Phi(x)$ is the high dimensional feature space, which is non-linearly mapped from the input space x. The coefficients w and b are estimated according to the process of risk minimization. The goal of this risk function is to find a function that has at most ε deviation from the actual values in all the training data points, using the formula:

$$R_{SVMs(C)} = C\frac{1}{n}\sum_{i=1}^{n} L_{\varepsilon}(d_i, y_i) + \frac{1}{2}\|w\|^2$$

The first and second terms in the formula above are the empirical risk error and the regularized term respectively. ε (epsilon) is called the tube size of SVMs, and C is the regularization constant determining the trade-off between the empirical error and the regularized term.

In this work, the kernel used is polynomial, which is of the form:

$$K(x,y) = (x^T y + 1)^d$$

and the error, designated by ε, was set to 0.2. The list below summarizes the optimized parameters.

- C = 450;
- lambda = 1e-7;
- epsilon = 0.2;
- kerneloption = 0.30;
- kernel = 'poly';
- verbose = 1;

4.1.3 Type-2 Fuzzy Logic

Interval Type-2 Fuzzy Sets with Gaussian Membership Functions are the most widely used Type-2 Fuzzy Sets because they are simple to use and because, at present, it is very difficult to justify the use of any other kind. When the Type-2 Fuzzy Sets are Interval Type-2 Fuzzy Sets, all secondary grades (flags) are equal to 1.

For the Type-2 Fuzzy Logic System, rules were extracted directly from the input data. This option was preferred over the extraction of rules from a subset of the data, because all data points are completely represented in the inference system. This leads to more time spent in implementation, but better accuracy and efficiency.

To be able to use Type-2 Fuzzy Logic System effectively, the following steps need to be taken:

- Perform the set-theoretic operations of union, intersection, and complement on Type-2 Sets.
- Know the properties (e.g. commutativity, associativity and identity laws) of membership grades of Type-2 Sets.
- Deal with Type-2 Fuzzy Relations and their compositions.

- Perform type reduction and defuzzification to obtain a set-valued or crisp output from the FLS.

4.1.3.1 Inferencing in Type-2 Fuzzy Logic

Generally, we can consider a dataset having p inputs and $x_1 \in X_1$, $x_2 \in X_2$, …, $x_p \in X_p$ and $y \in Y$. The rules are of the general form:

Rl: IF x_1 is F_1^l and x_2 is F_2^l and … and x_p is F_p^l THEN y is G^l

This rule represents a Type-2 Fuzzy relation between the input space X_1 x X_2 x … x X_p and the output space Y of the system. We denote the membership function of this Type-2 relation as:

$$\mu_{F_1^l x \ldots x F_p^l \rightarrow G^l}(x, y)$$

where F_1^l x …x F_p^l denotes the Cartesian product of F_1^l, F_2^l … F_p^l and x = {x_1, x_2, …, x_p}.

4.1.3.2 Type Reduction

The output set corresponding to each rule of the Type-2 FLS is a Type-2 set. There is then the need to reduce the type from 2 to 1, in order to give room for defuzzification. The type-reducer combines all these output sets:

$$C_A = \frac{\sum_{i=1}^{N} X_i \mu_A(x_i)}{\sum_{i=1}^{N} \mu_A(x_i)}$$

This would then be converted to a Type-2 Set by applying the Extension Principle, details of which can be found in [44].

The type-reduced set of a Type-2 FLS is the centroid of a Type-2 output set for the FLS. Consequently, each element of the type-reduced set is the centroid of some Type-1 Set embedded in the output set of the Type-2 FLS. Each of these embedded sets can be thought of as an output set of some Type-1 FLS and, correspondingly, the Type-2 FLS can be thought of as a collection of many different Type-1 FLSs. Each of these Type-1 FLSs is embedded in the Type-2 FLS. So the type-reduced set is a collection of the outputs of all the Type-1 FLSs embedded in the Type-2 FLS, and it lets us represent the output of the Type-2 FLS as a fuzzy set rather than as a crisp number.

4.1.3.3 Defuzzification

We defuzzify the type-reduced set to get a crisp output from the Type-2 FLS. The most natural way of doing this seems to be by finding the centroid of the type-reduced set. Finding the centroid is equivalent to finding a weighted average of the outputs of all the Type-1 FLSs embedded in the Type-2 FLS, where the weights correspond to the memberships in the type-reduced set. If the type-reduced set for an input is discrete and consists of points, the expression for its centroid is:

$$C_Y(x) = \frac{\sum_{i=1}^{N} y_k \mu_Y(y_k)}{\sum_{i=1}^{N} \mu_Y(y_k)}$$

If the type-reduced set has only one point having unity membership, and if we wish to reduce the computational complexity, we may decide that a more straightforward choice for the defuzzified value is the unity membership point in the type-reduced set. Choosing the unity membership point, however, means that we are doing away with all the Type-2 analysis and are choosing the output corresponding to only the principal membership function Type-1 FLS that is embedded in the Type-2 FLS. Since the unity height point conveys no information about membership function uncertainties, it cannot sensibly be used as the crisp output unless the type-reduced set is convex and symmetric, in which case the unity height point is the same as the centroid. In general, for arbitrary membership functions, the type-reduced set is not symmetrical, and the centroid location is different from the location of the unity height point.

The list below summarizes the remaining optimized parameters of th Type-2 Fuzzy block:

- sn2 = sn1; This is the standard deviation of the input data.
- alpha4=alpha = 0.1; This is the learning parameter.

The individual techniques were run separately. Then their components were combined in the hybrids and also run with the same input dataset. In order to ensure most fairness in the results, several iterations were made and the average values of the results were taken. This is necessary due to the behavior of the Stratified Sampling approach used to divide the input data into training and testing sets. Since the input data is randomized during the division processes, hence, slightly different results are obtained for each run of the experiments.

The results of the prediction processes for Porosity and Permeability are presented in the following sections.

4.2 Results for the Prediction of Porosity

Tables 17 – 22 present the result of the prediction of Porosity for the three wells in site 1 and three wells in site 2. These are followed by the line graphs showing the actual and the predicted outputs for the respective wells in figures 11 – 70.

Site 1, Well 1 (Porosity) – 415 points – 285 for Training – 124 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
SVM	0.820348	0.94502	7.54717	2.80199	15.458333	0.000000
FN	0.835855	0.957491	6.17685	4.15040	0.098958	0.000000
Fuzzy Logic	0.840697	0.816021	6.85104	7.52180	155.395833	55.937500
Hybrid – FFS	0.920608	0.969179	7.06432	3.72873	60.979167	9.093750
Hybrid – FSF	0.916415	0.957003	6.61915	5.67851	61.562500	8.890625

Table 17: Result of the Porosity prediction Site 1, Well 1

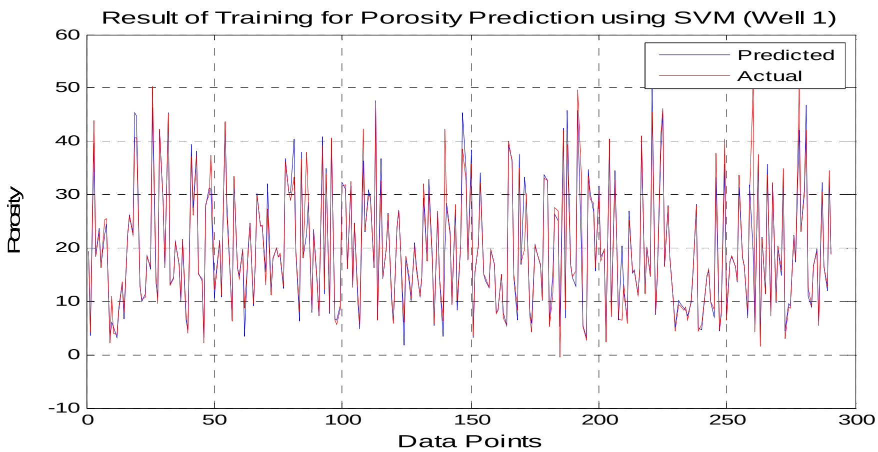

Figure 11: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (SVM Training)

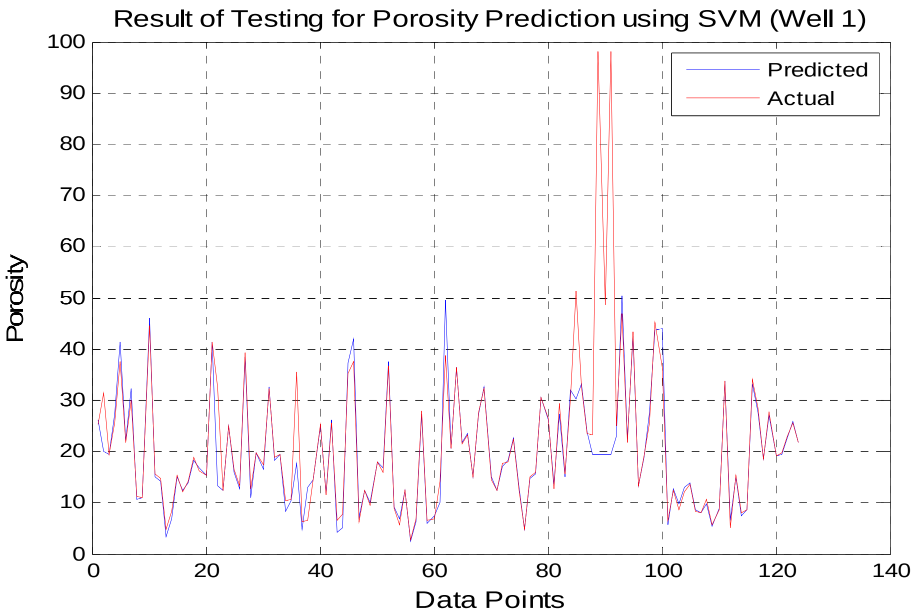

Figure 12: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (SVM Testing)

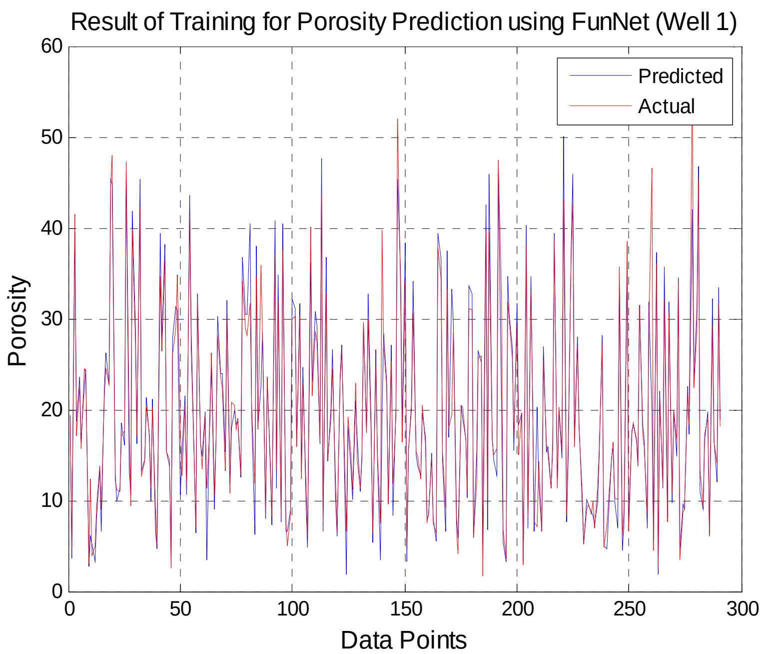

Figure 13: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (FN Training)

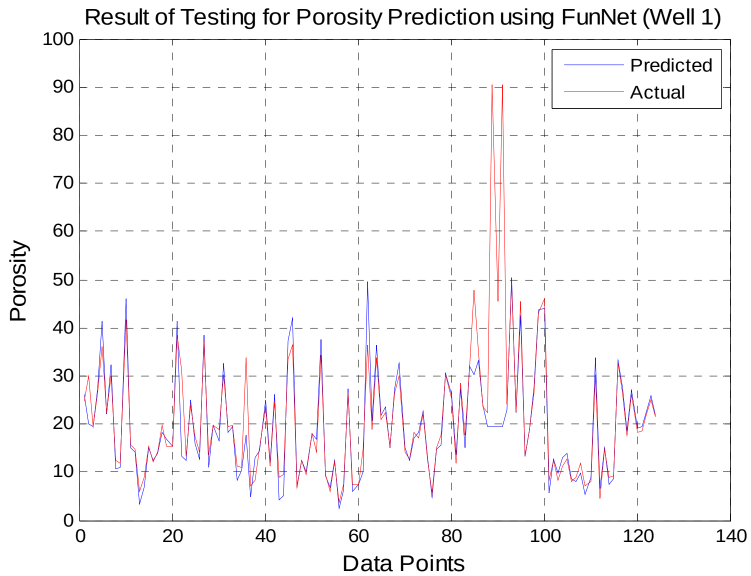

Figure 14: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (FN Testing)

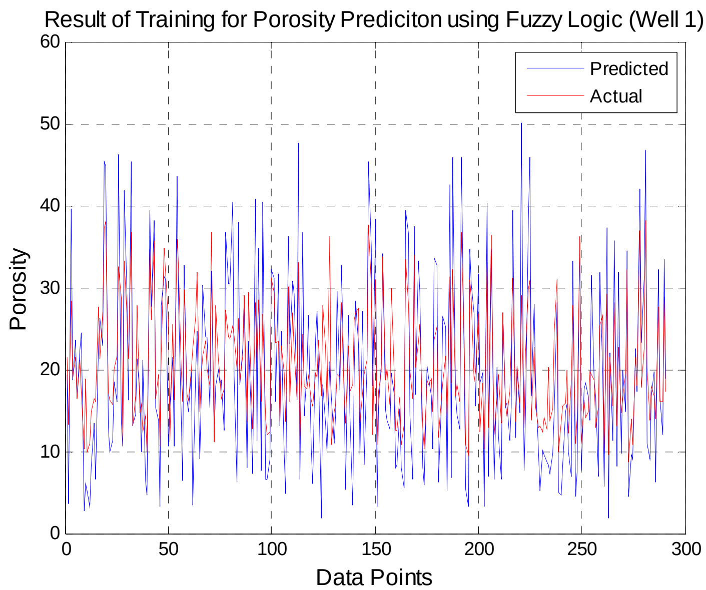

Figure 15: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (Fuzzy Logic Training)

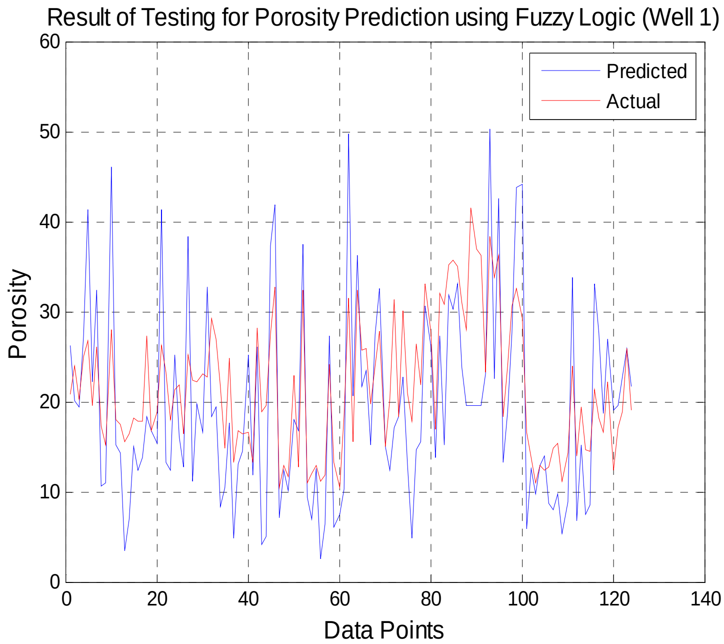

Figure 16: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (Fuzzy Logic Testing)

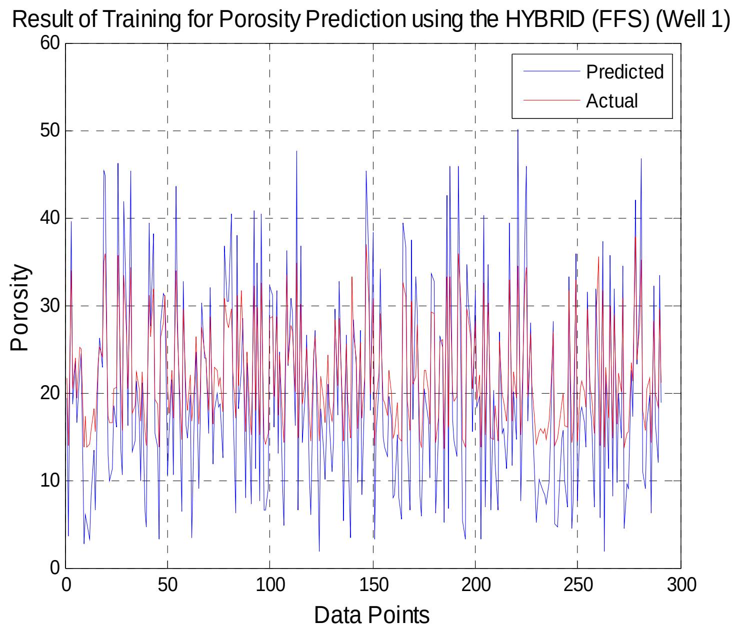

Figure 17: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (FFS Training)

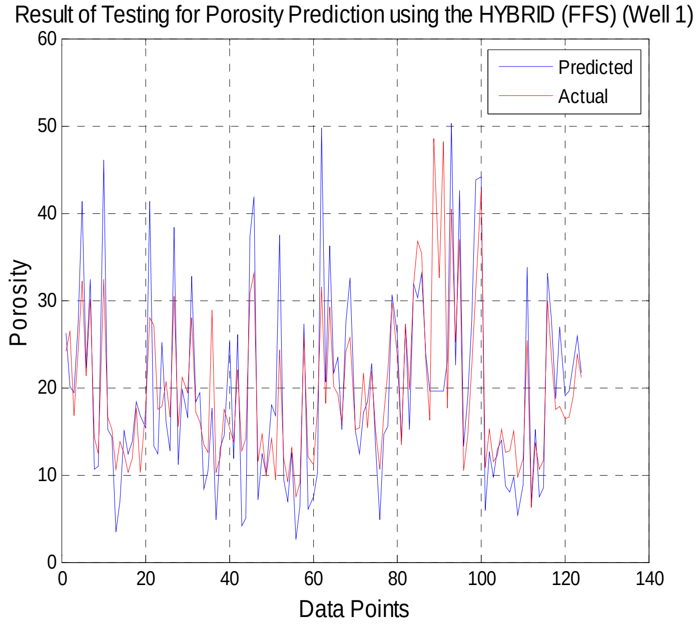

Figure 18: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (Hybrid (FFS) Testing)

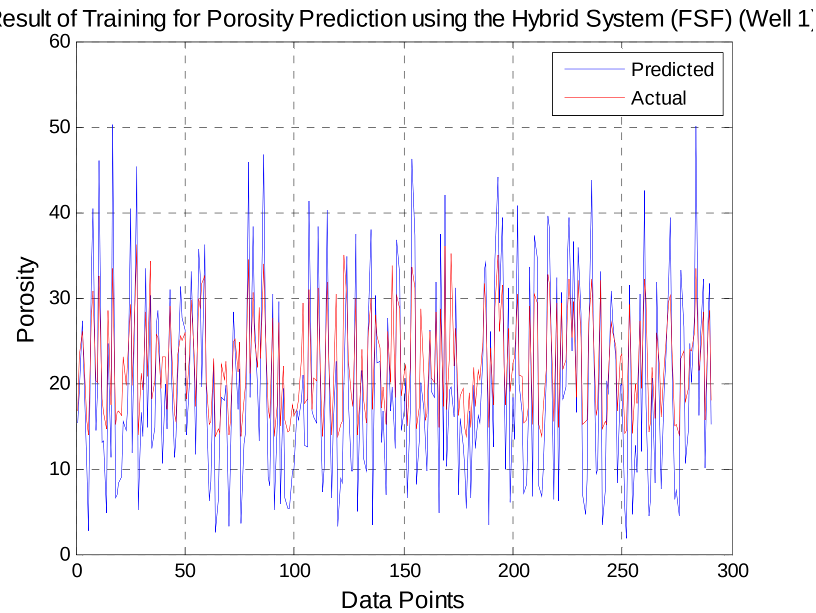

Figure 19: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (FSF Training)

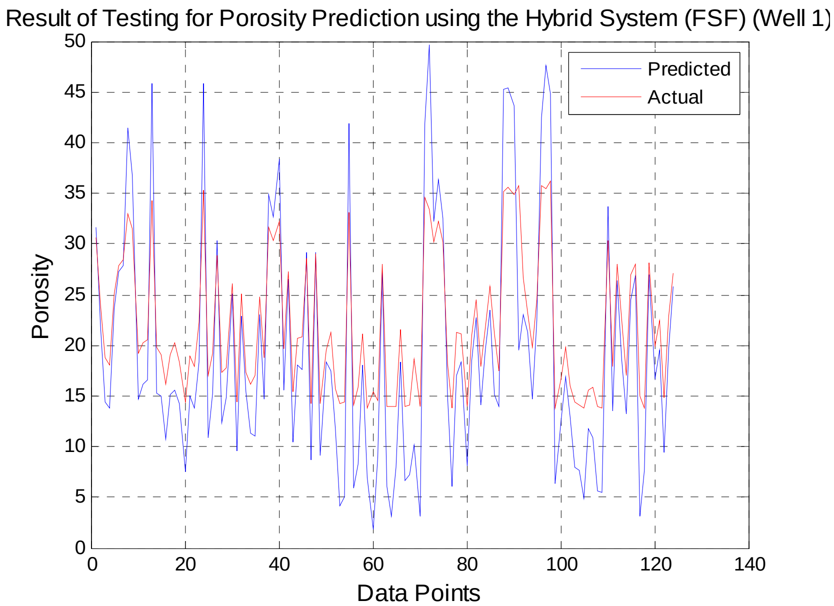

Figure 20: Plot of Actual vs. Predicted Porosity for Site 1, Well 1 (FSF) Testing)

Site 1, Well 2 (Porosity) – 285 points – 200 for Training – 85 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
SVM	0.806304	0.775851	6.75723	7.17699	7.354167	0.000000
FN	0.803918	0.775465	6.77203	7.18608	0.093750	0.000000
Fuzzy Logic	0.798557	0.723302	7.31978	7.69430	71.526042	25.817708
Hybrid – FFS	0.82147	0.80758	9.18052	7.09860	28.442708	4.411458
Hybrid – FSF	0.8147	0.813319	9.09662	9.45112	31.567708	4.296875

Table 18: Result of the Porosity prediction Site 1, Well 2

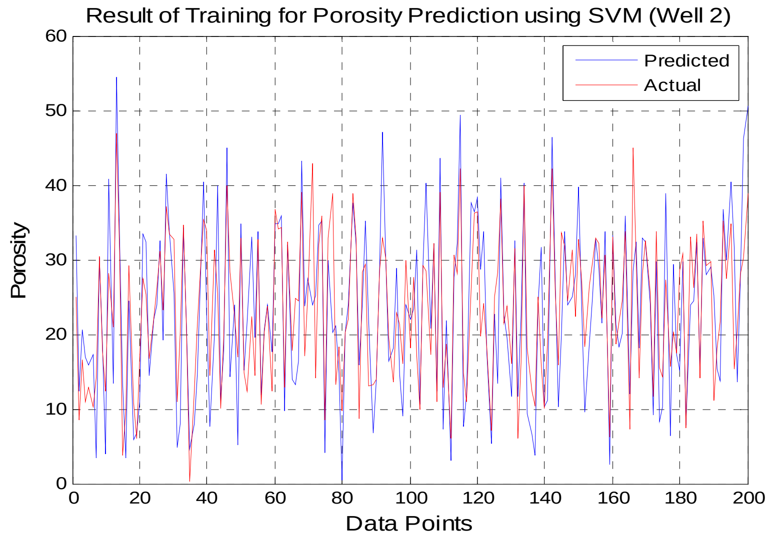

Figure 21: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (SVM Training)

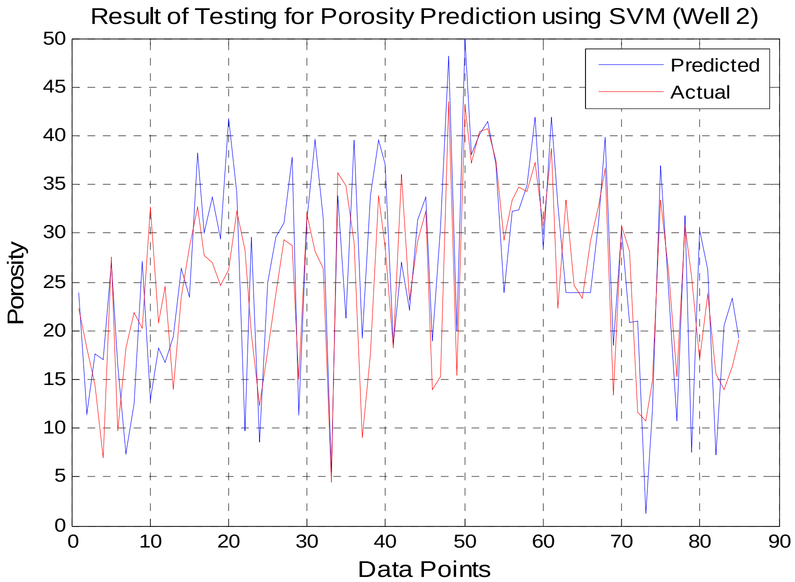

Figure 22: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (SVM Testing)

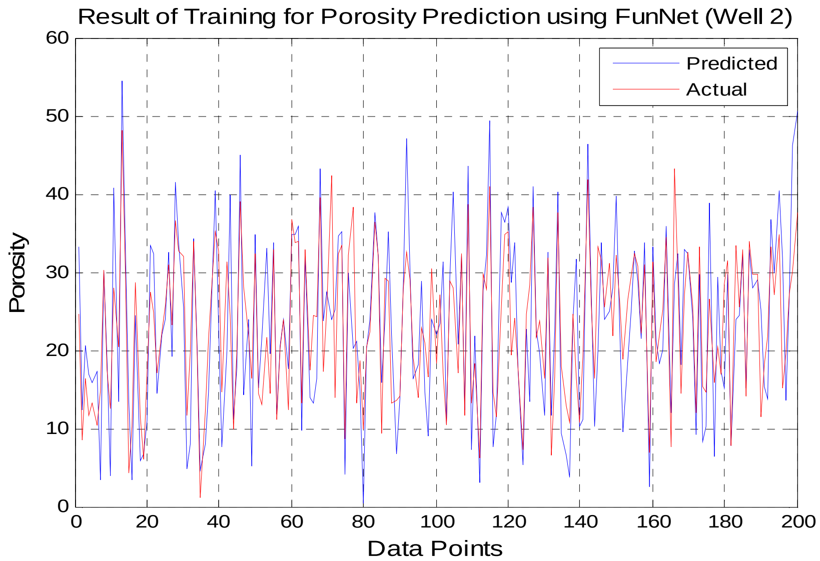

Figure 23: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FN Training)

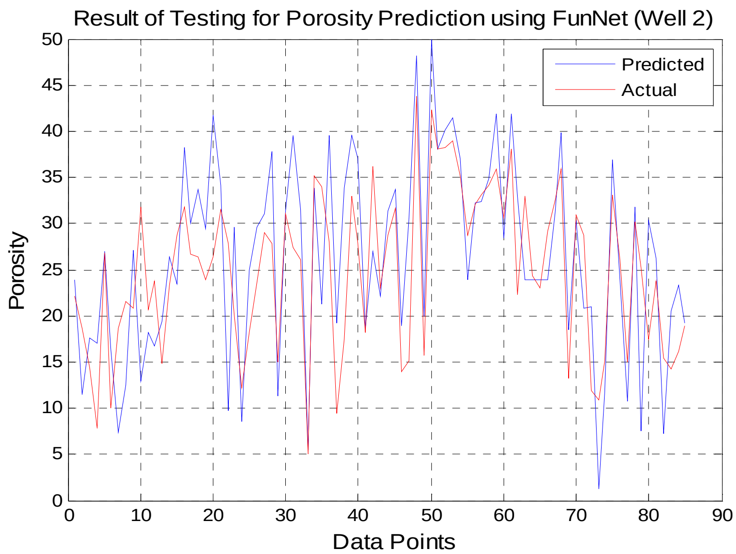

Figure 24: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FN Testing)

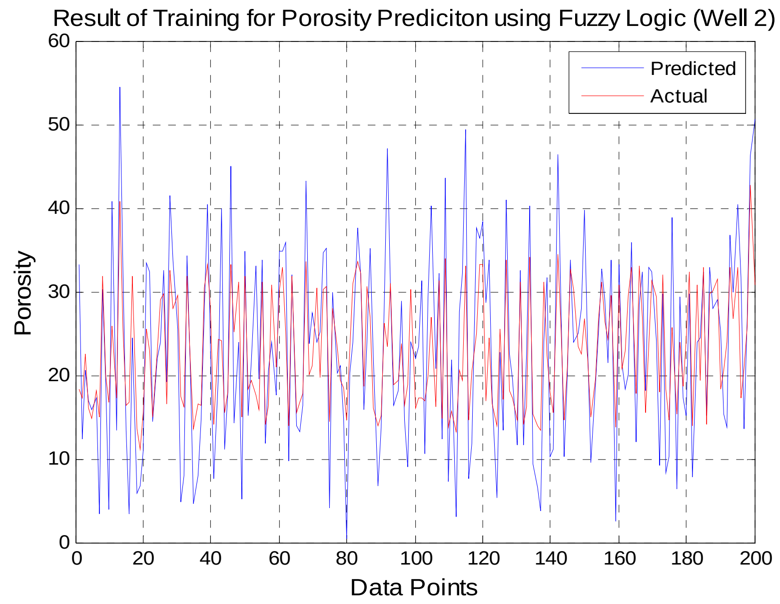

Figure 25: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FL Training)

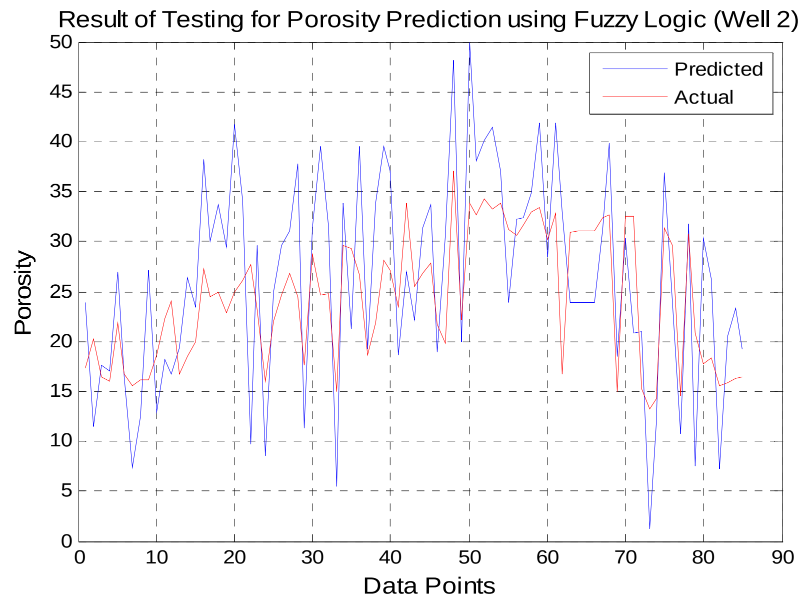

Figure 26: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FL Testing)

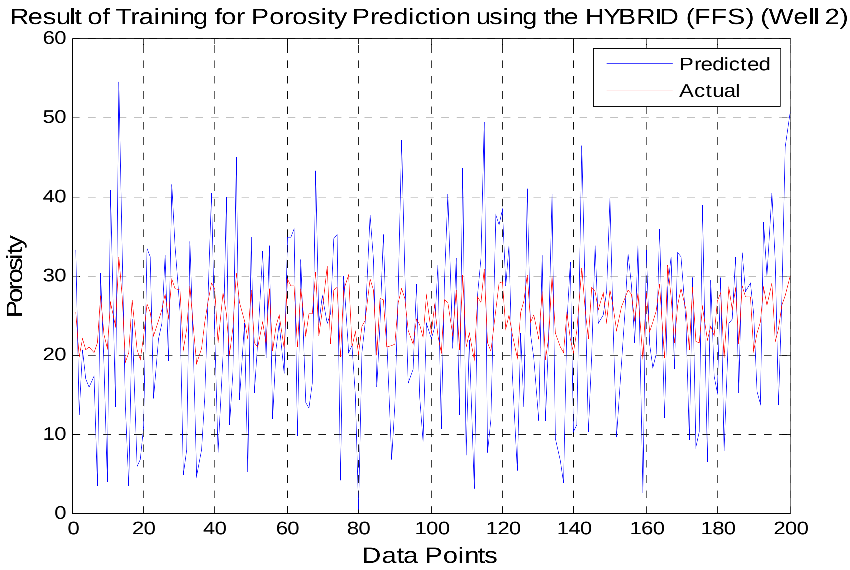

Figure 27: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FFS Training)

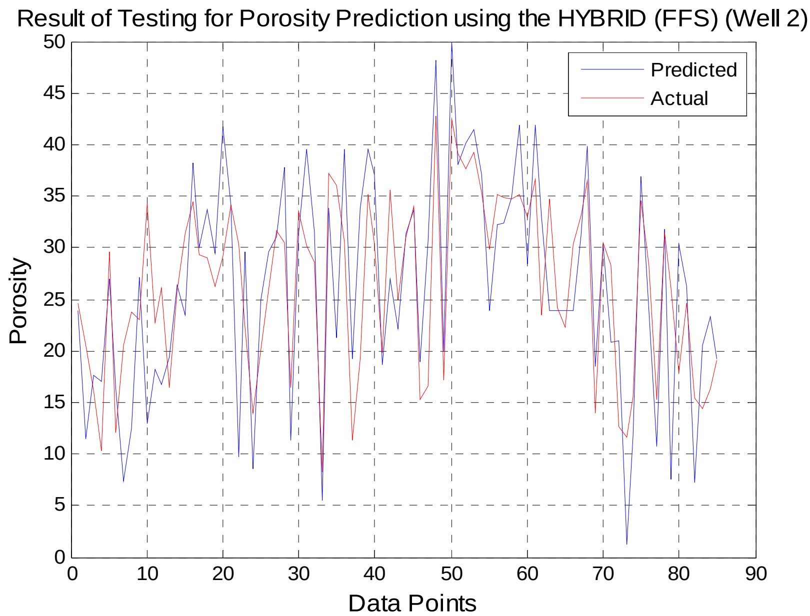

Figure 28: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FFS Testing)

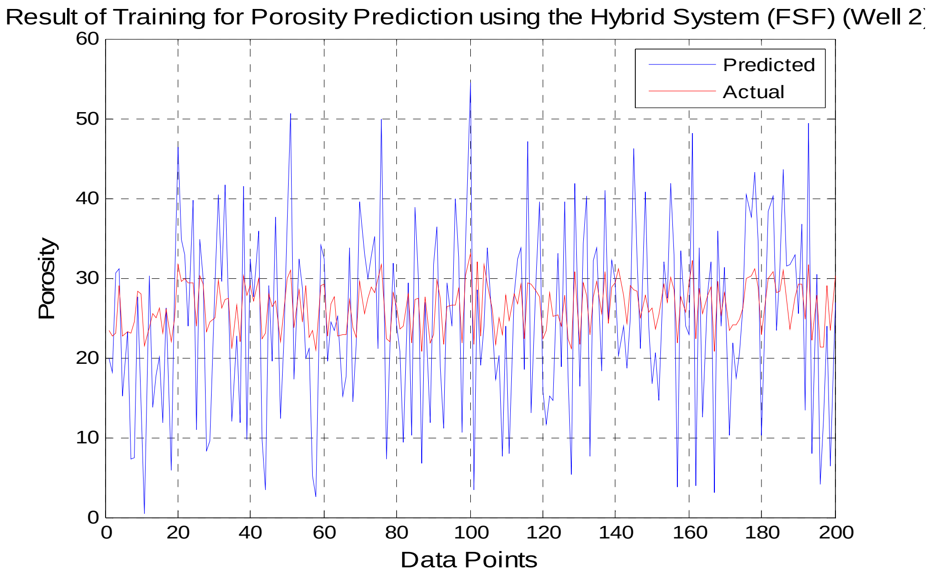

Figure 29: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FSF Training)

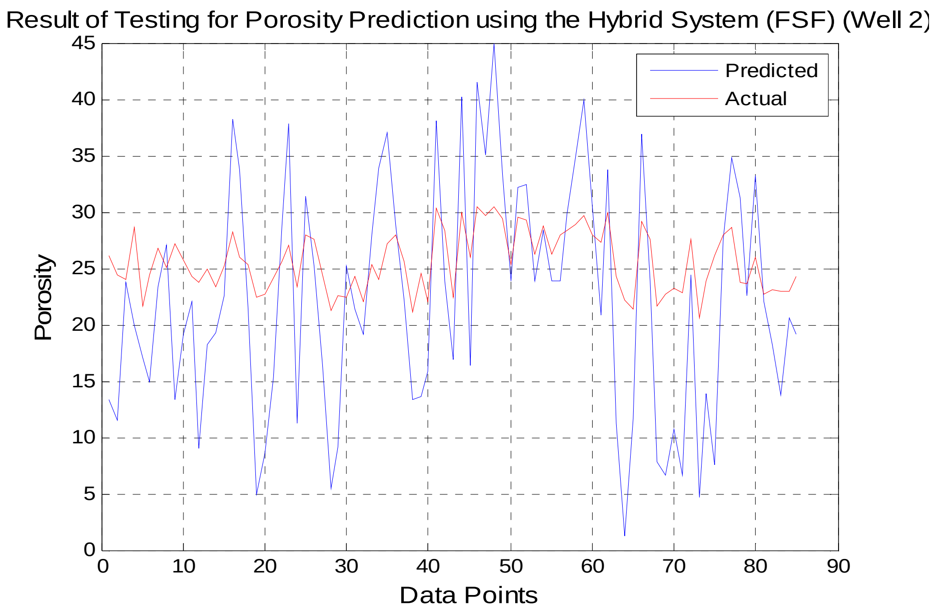

Figure 30: Plot of Actual vs. Predicted Porosity for Site 1, Well 2 (FSF Testing)

Site 1, Well 3 (Porosity) - 23 points – 16 for Training – 7 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
SVM	**0.980730**	**0.898397**	**1.64195**	**2.95456**	**0.315625**	**0.000000**
FN	**0.824680**	**0.803017**	**4.75388**	**6.26507**	**0.062500**	**0.000000**
Fuzzy Logic	**0.910924**	**0.599756**	**4.26323**	**7.04103**	**0.518750**	**0.129688**
Hybrid – FFS	**0.93055**	**0.914020**	**6.37047**	**3.34832**	**0.493750**	**0.042188**
Hybrid – FSF	**0.920961**	**0.928830**	**6.81454**	**8.32623**	**0.471094**	**0.051042**

Table 19: Result of the Porosity prediction Site 1, Well 3

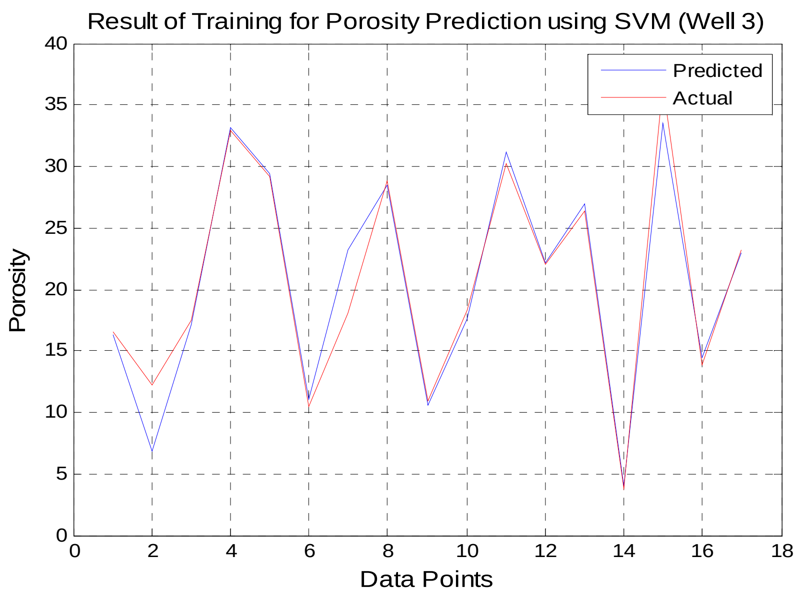

Figure 31: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (SVM Training)

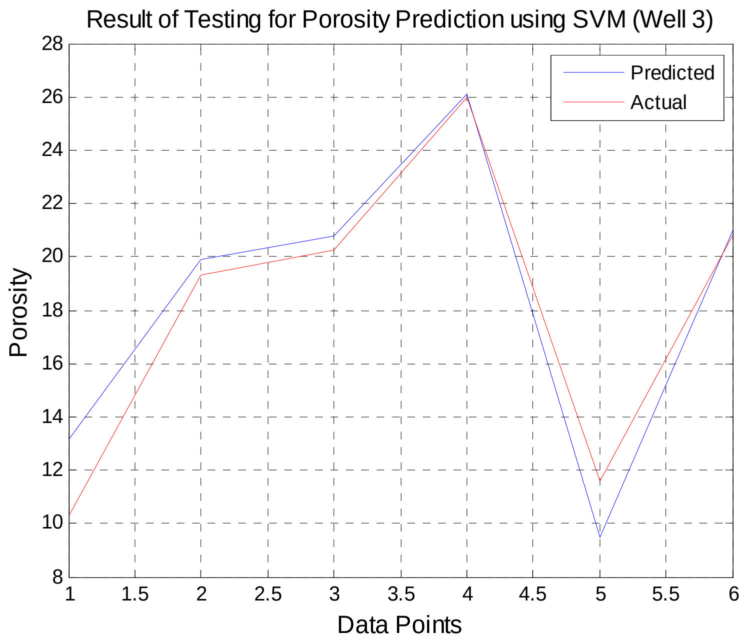

Figure 32: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (SVM Testing)

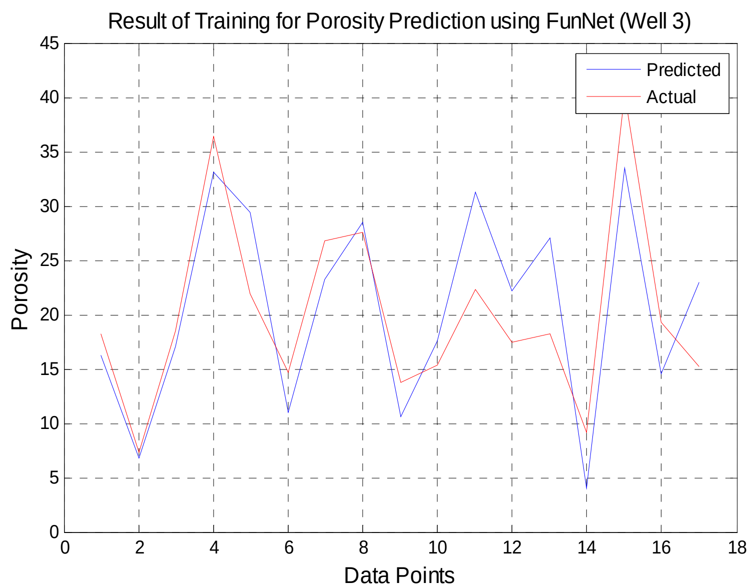

Figure 33: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FN Training)

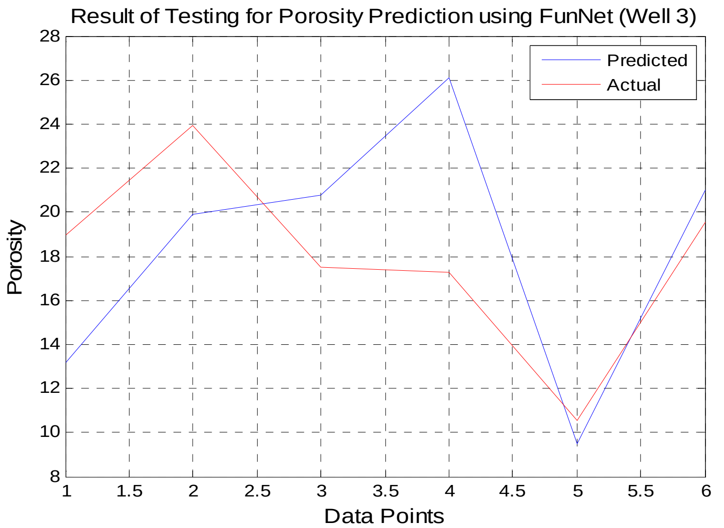

Figure 34: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FN Testing)

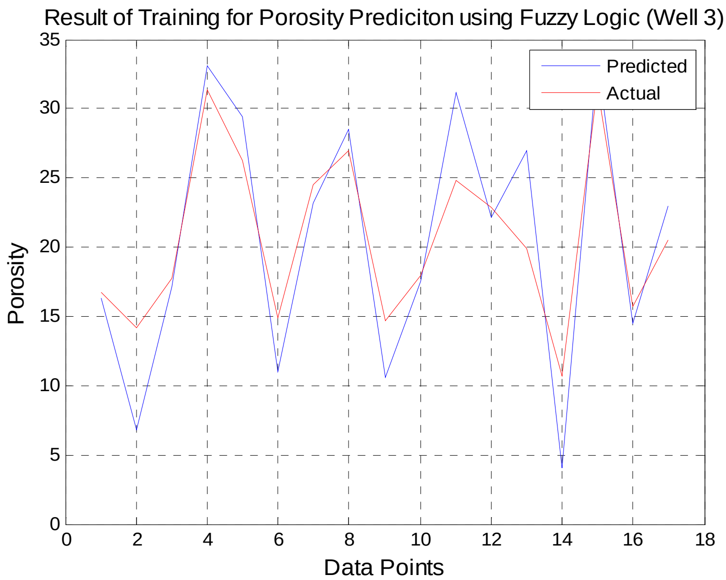

Figure 35: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FL Training)

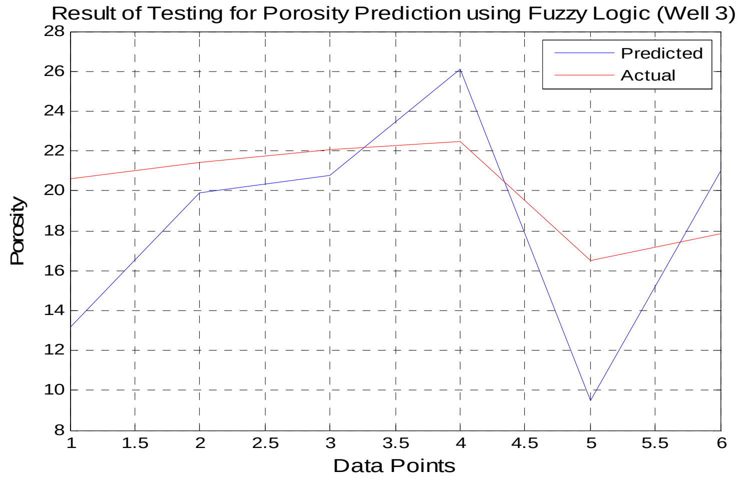

Figure 36: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FL Testing)

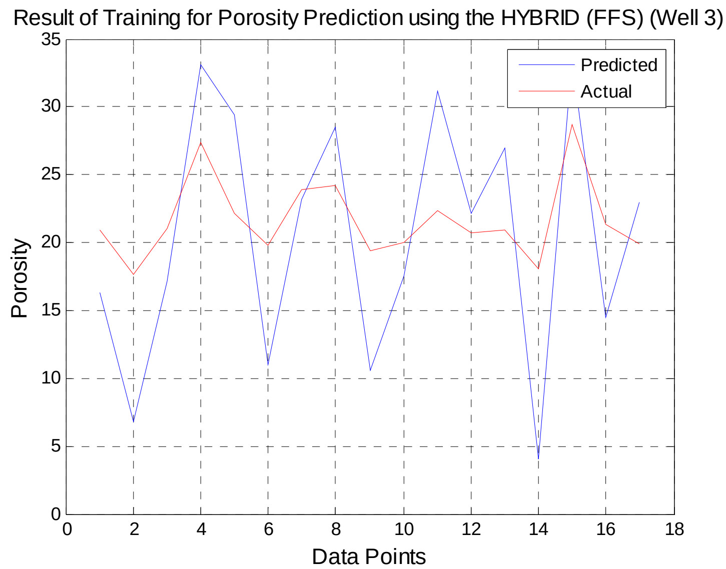

Figure 37: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FFS Training)

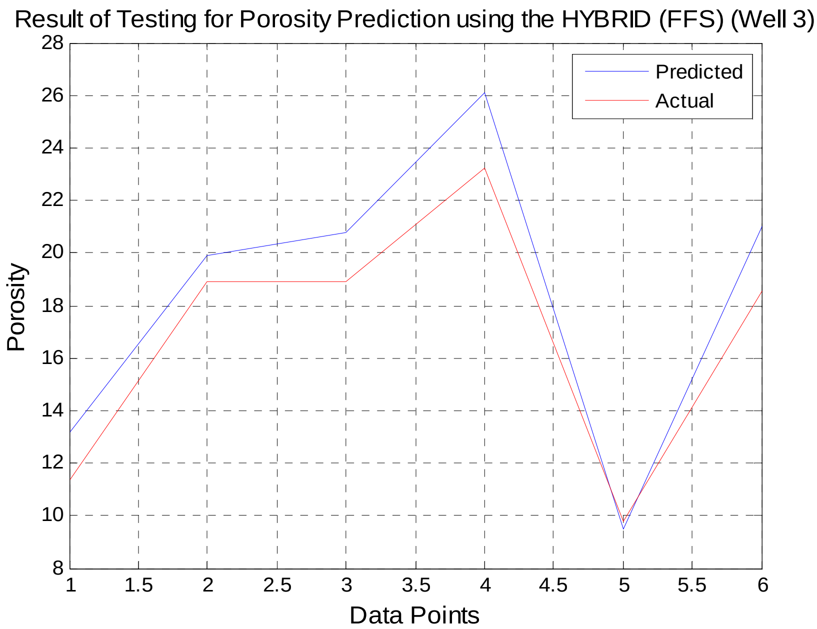

Figure 38: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FFS Testing)

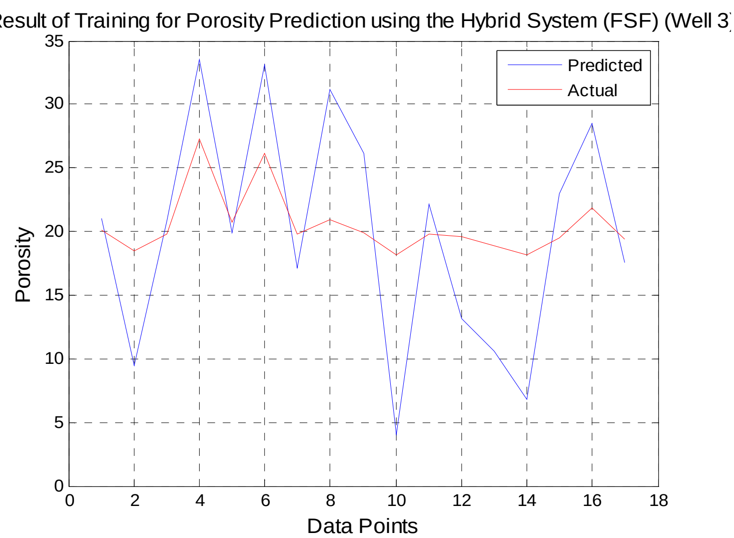

Figure 39: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FSF Training)

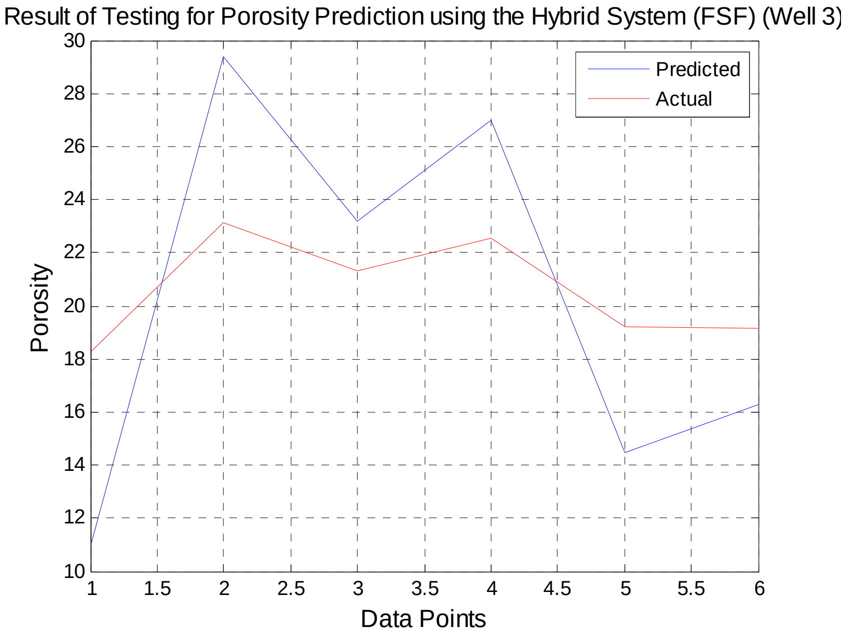

Figure 40: Plot of Actual vs. Predicted Porosity for Site 1, Well 3 (FSF Testing)

Site 2, Well 1 (Porosity) - 293 points – 205 for Training – 88 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
SVM	**0.886045**	**0.920350**	**2.87549**	**2.55978**	**7.843750**	**0.005208**
FN	**0.882898**	**0.918169**	**2.87489**	**2.61417**	**0.088542**	**0.000000**
Fuzzy Logic	**0.876406**	**0.890971**	**3.17196**	**2.94807**	**64.369792**	**23.234375**
Hybrid – FFS	**0.887868**	**0.926937**	**3.46602**	**2.72990**	**29.885417**	**4.447917**
Hybrid – FSF	**0.889117**	**0.936937**	**3.44770**	**3.35107**	**36.145833**	**5.427083**

Table 20: Result of the Porosity prediction Site 2, Well 1

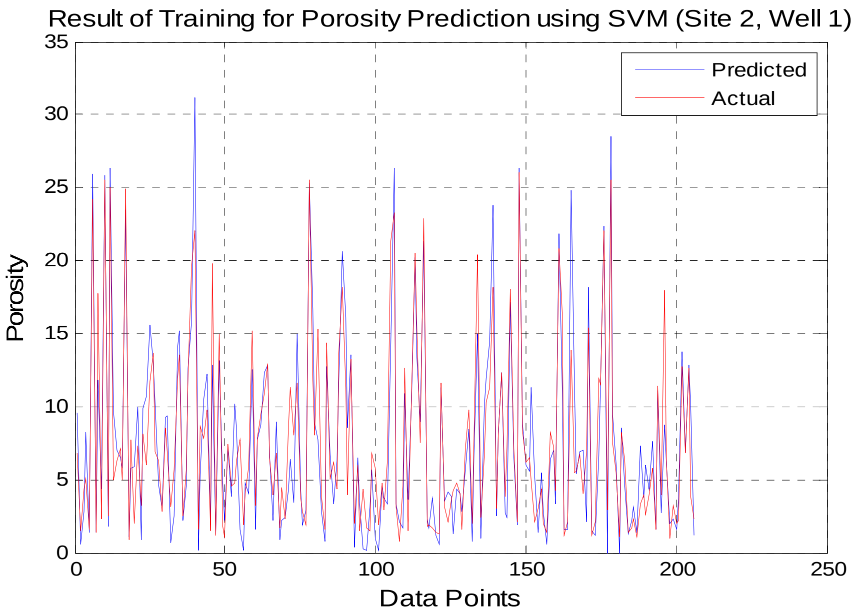

Figure 41: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (SVM Training)

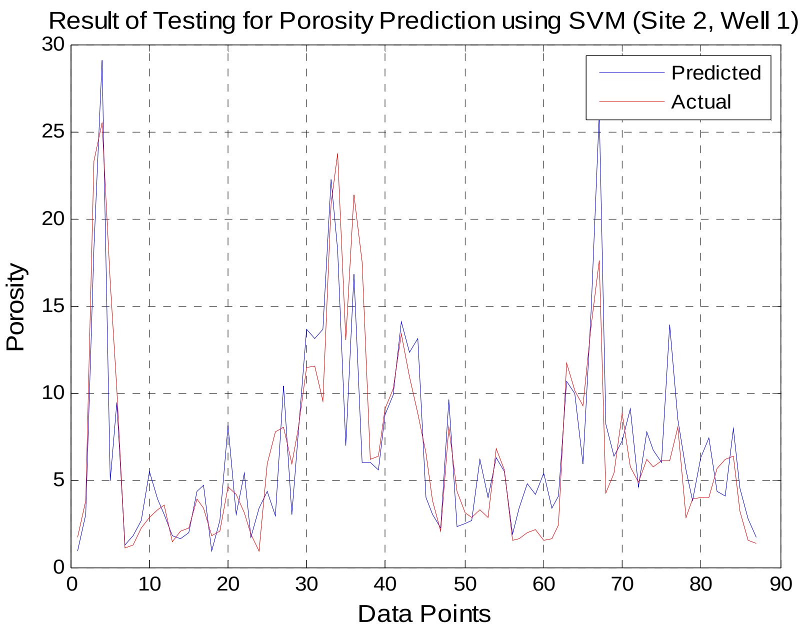

Figure 42: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (SVM Testing)

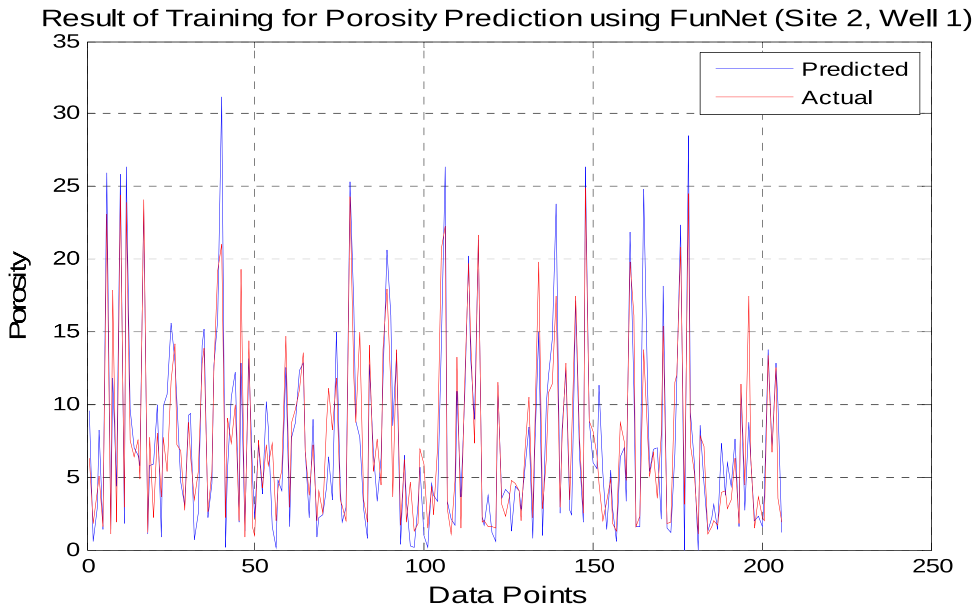

Figure 43: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FN Training)

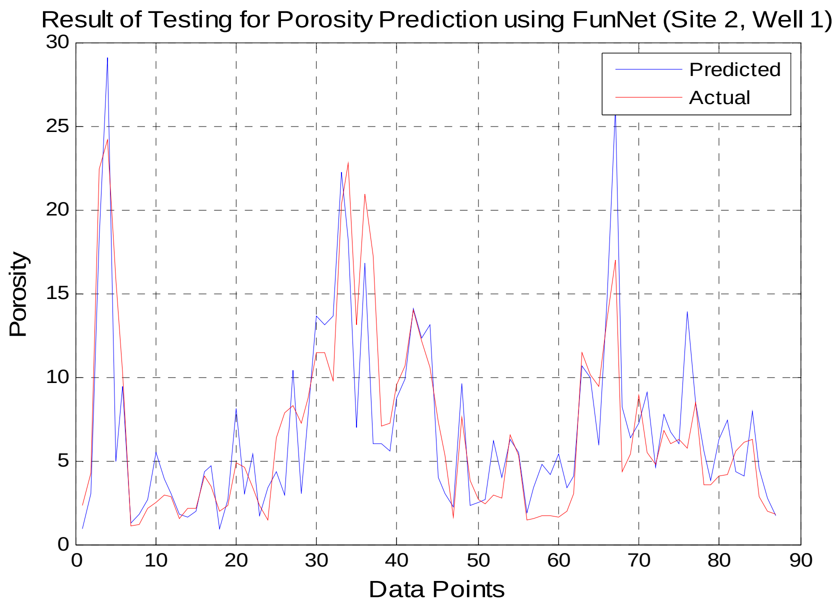

Figure 44: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FN Testing)

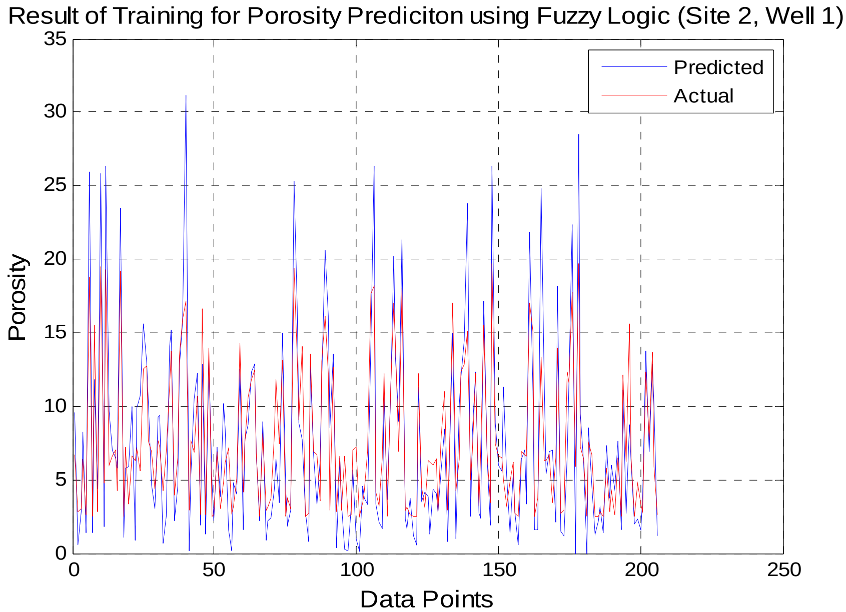

Figure 45: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FL Training)

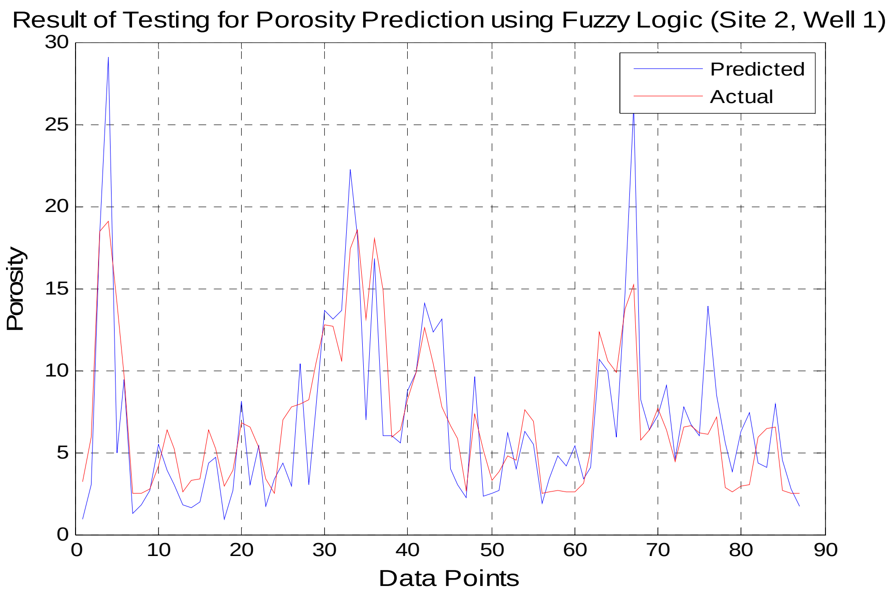

Figure 46: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FL Testing)

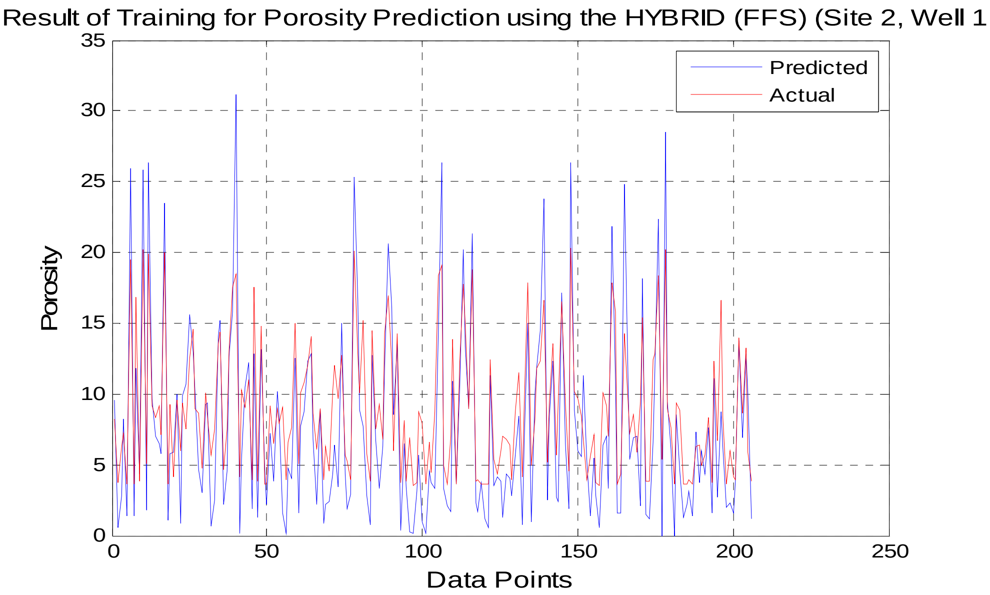

Figure 47: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FFS Training)

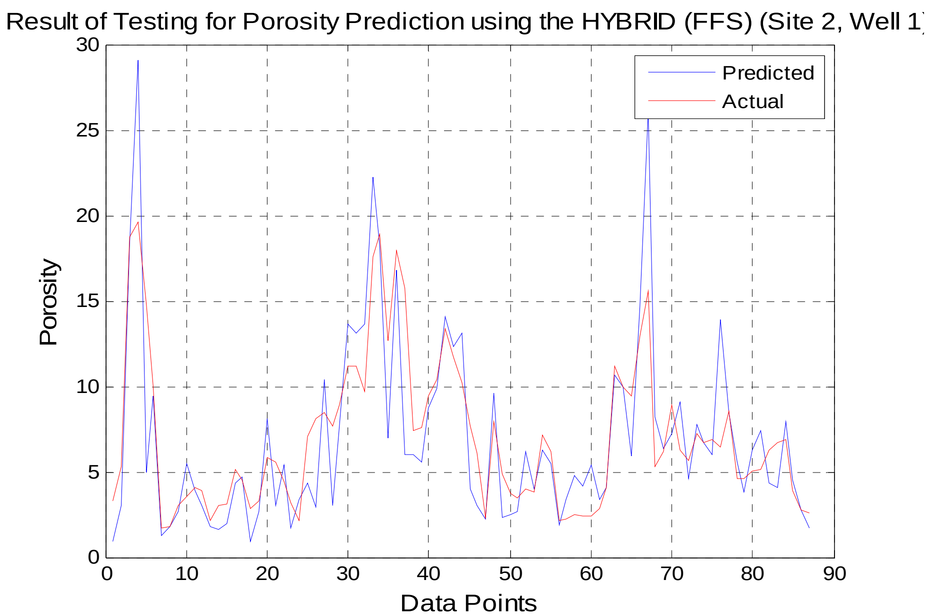

Figure 48: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FFS Testing)

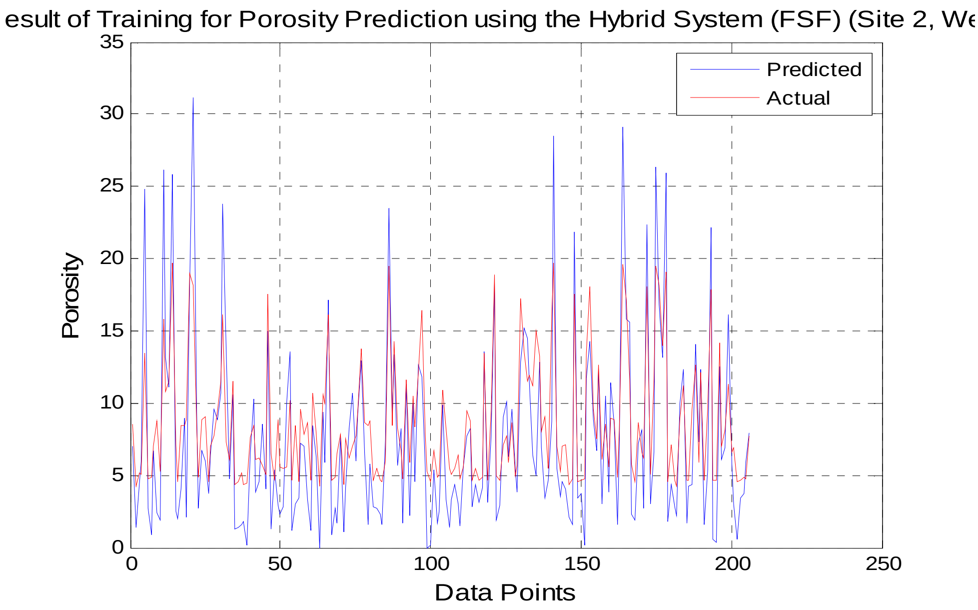

Figure 49: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FSF Training)

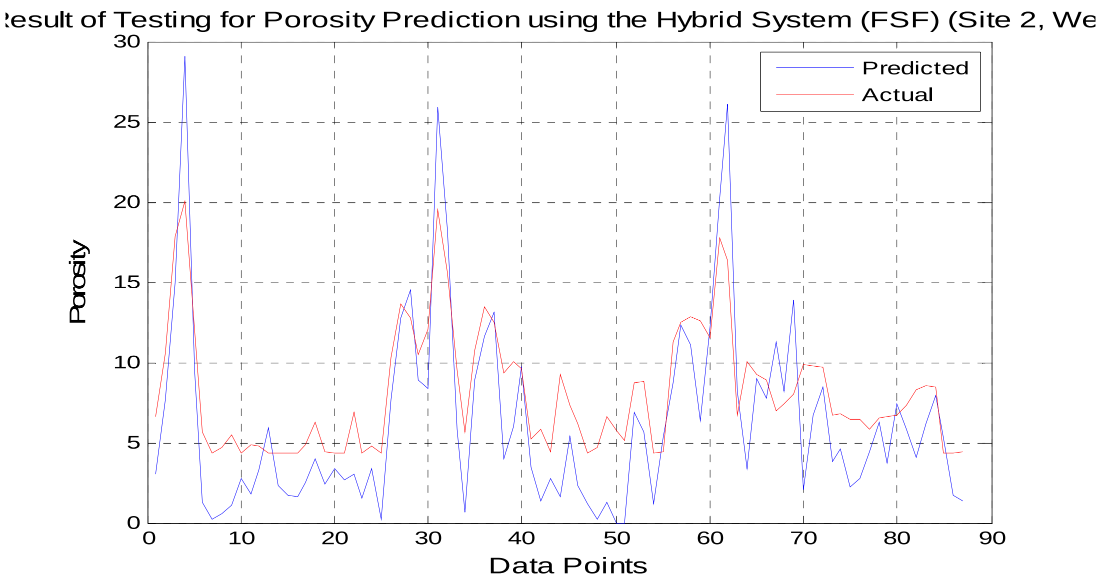

Figure 50: Plot of Actual vs. Predicted Porosity for Site 2, Well 1 (FSF Testing)

Site 2, Well 2 (Porosity) - 183 points – 128 for Training – 55 for Testing						
Model	Correlation Coefficient		RMSE		Execution Time (s)	
	Training	Testing	Training	Testing	Training	Testing
SVM	0.881959	0.854757	3.55750	3.66038	3.572917	0.005208
FN	0.880477	0.853532	3.54060	3.58458	0.098958	0.000000
Fuzzy Logic	0.868605	0.848657	3.83944	3.74305	26.937500	8.953125
Hybrid – FFS	0.878771	0.867322	3.98812	3.40882	12.406250	1.692708
Hybrid – FSF	0.875374	0.887909	4.04180	3.55275	12.973958	1.812500

Table 21: Result of the Porosity prediction Site 2, Well 2

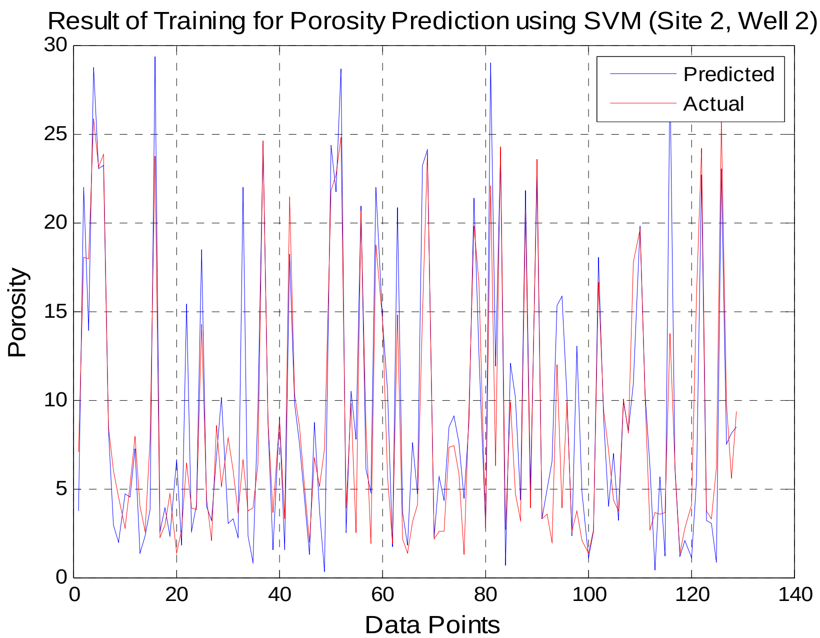

Figure 51: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (SVM Training)

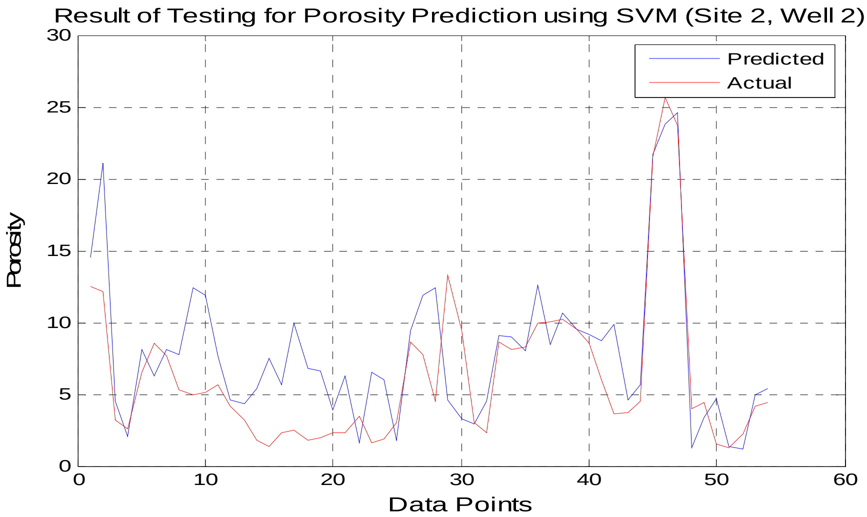

Figure 52: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (SVM Testing)

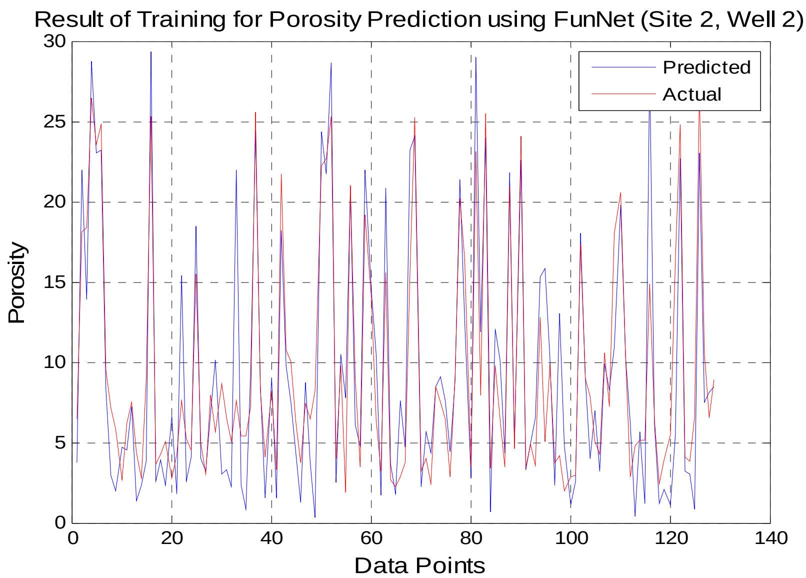

Figure 53: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FN Training)

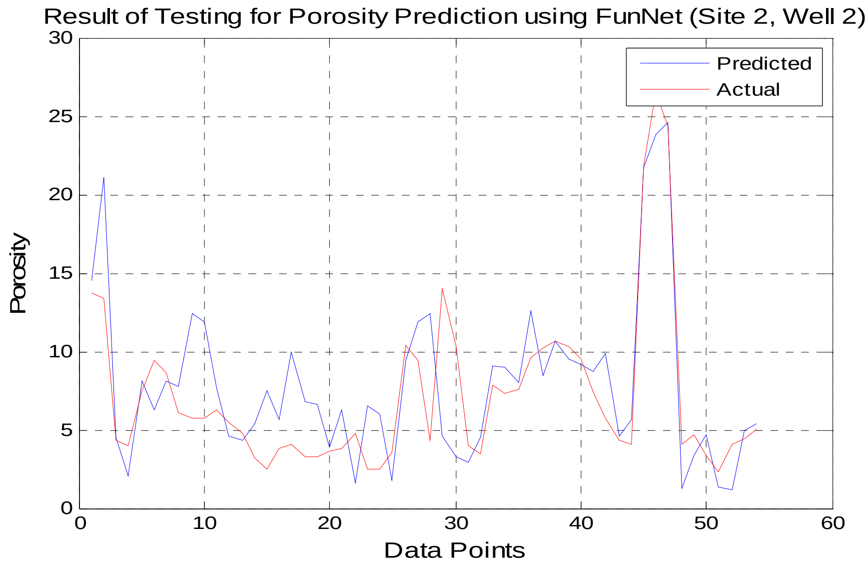

Figure 54: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FN Testing)

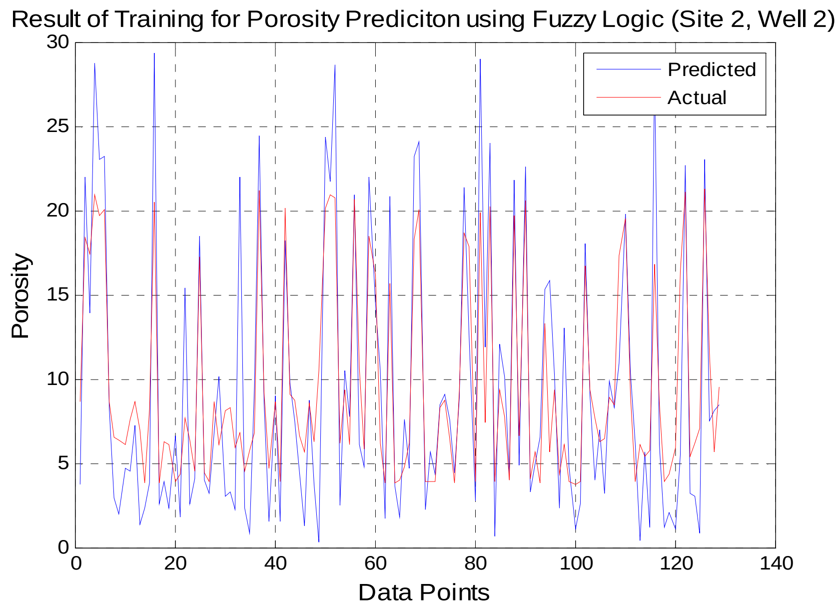

Figure 55: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FL Training)

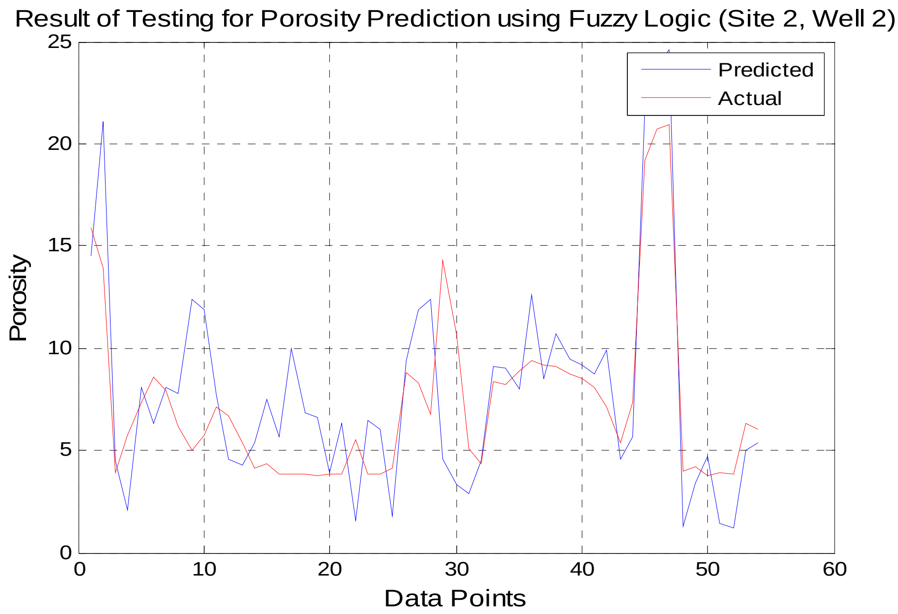

Figure 56: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FL Testing)

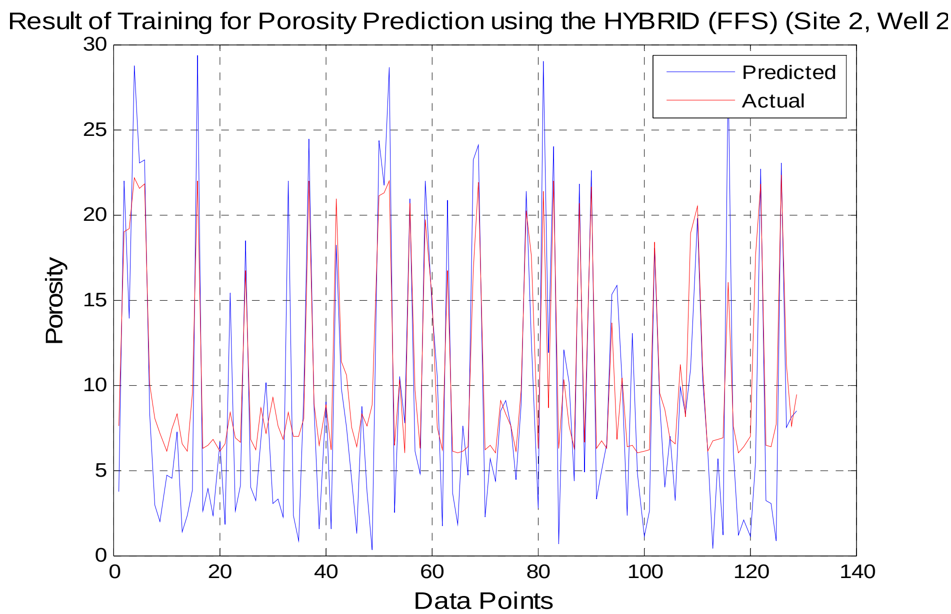

Figure 57: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FFS Training)

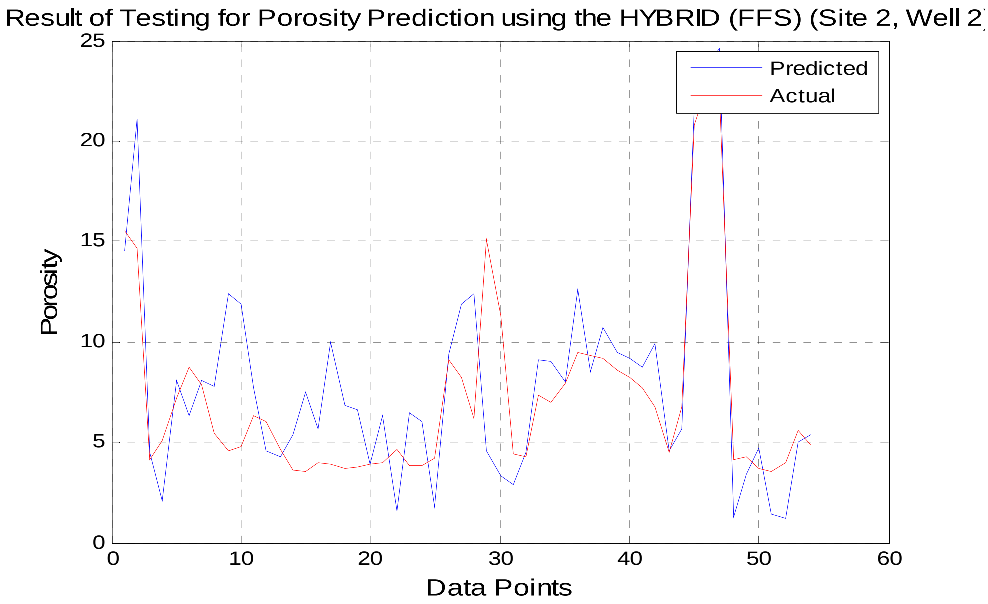

Figure 58: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FFS Testing)

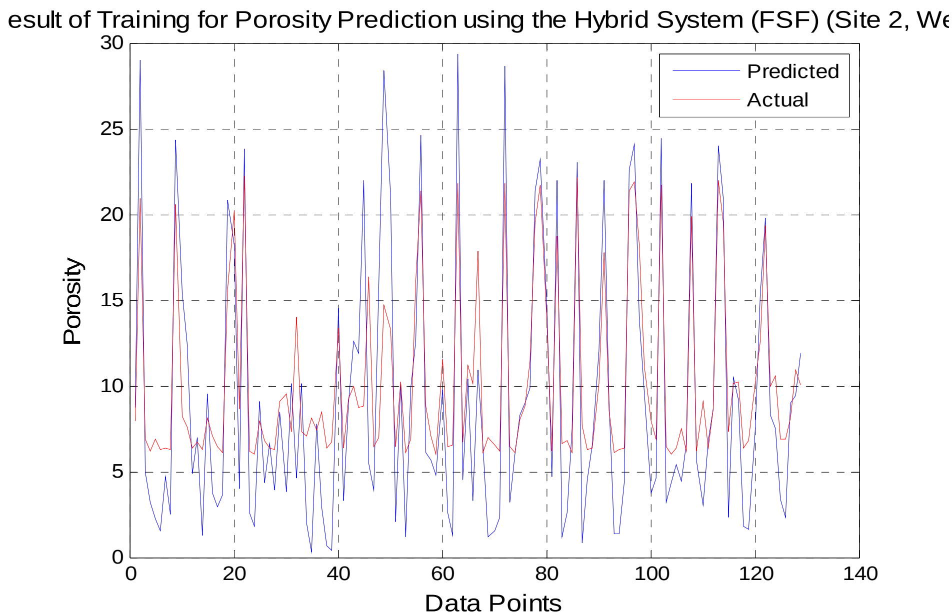

Figure 59: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FSF Training)

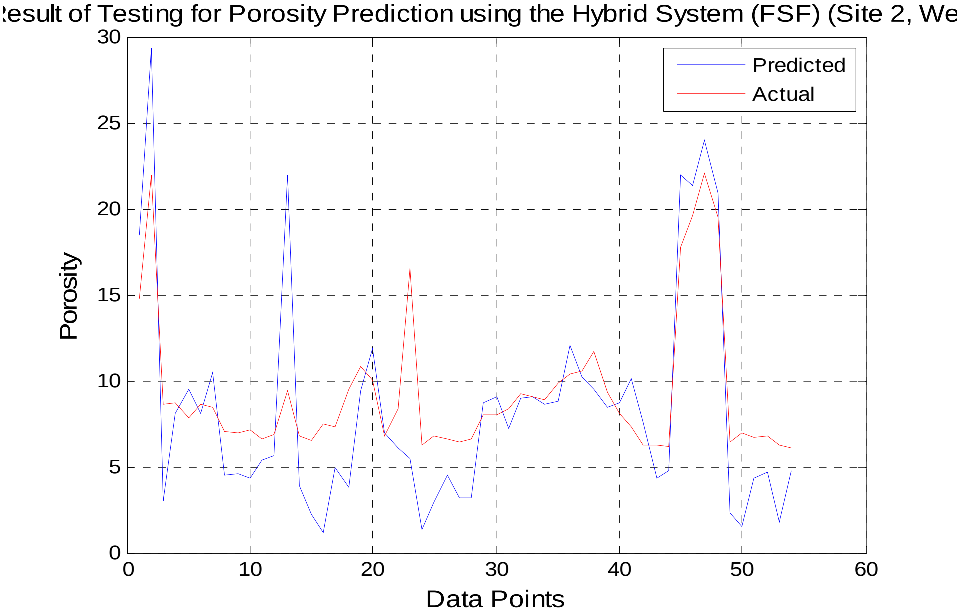

Figure 60: Plot of Actual vs. Predicted Porosity for Site 2, Well 2 (FSF Testing)

Site 2, Well 10 (Porosity) - 97 points – 68 for Training – 29 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Testing**	**Testing**	**Training**	**Testing**
SVM	**0.850715**	**0.907675**	**2.55871**	**2.77695**	**1.473958**	**0.000000**
FN	**0.851278**	**0.881427**	**2.49021**	**2.87829**	**0.078125**	**0.000000**
Fuzzy Logic	**0.848065**	**0.891743**	**2.57381**	**2.38829**	**8.083333**	**2.609375**
Hybrid – FFS	**0.873379**	**0.920106**	**2.56398**	**2.28792**	**3.786458**	**0.526042**
Hybrid – FSF	**0.865388**	**0.916027**	**2.76133**	**2.88573**	**3.928125**	**0.809375**

Table 22: Result of the Porosity prediction Site 2, Well 10

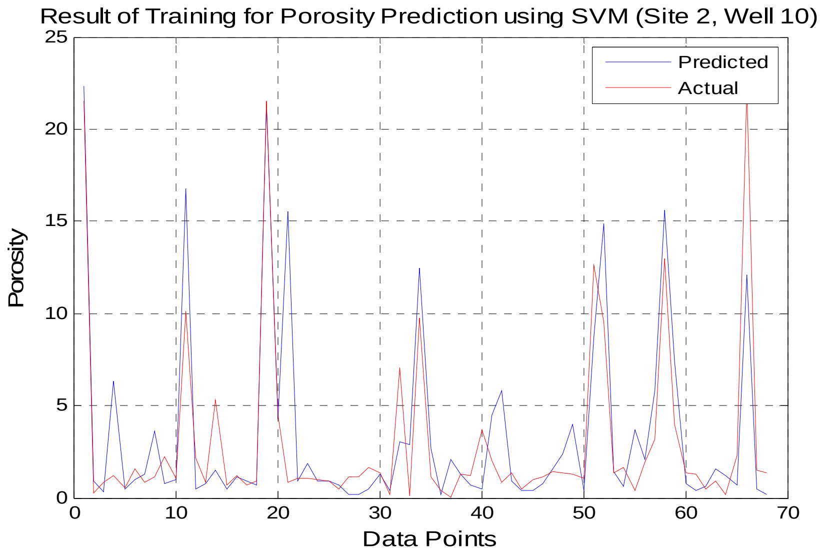

Figure 61: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (SVM Training)

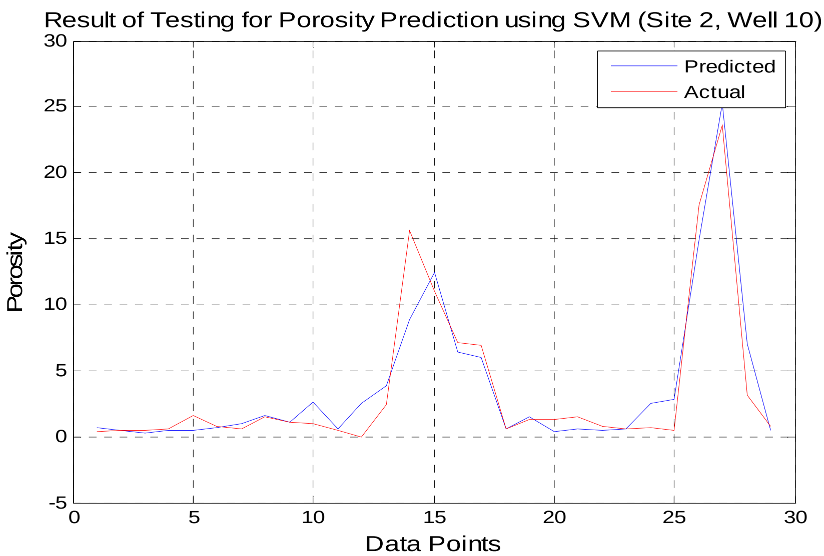

Figure 62: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (SVM Testing)

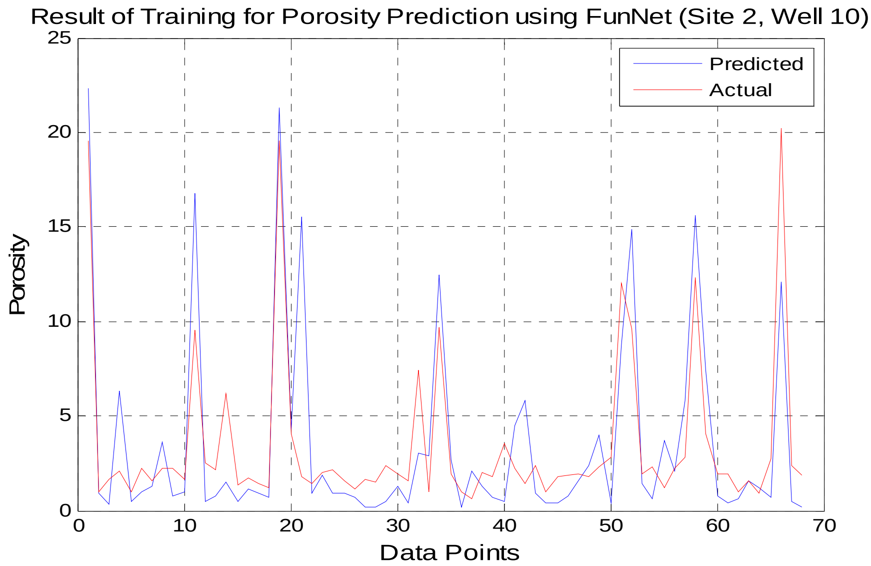

Figure 63: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FN Training)

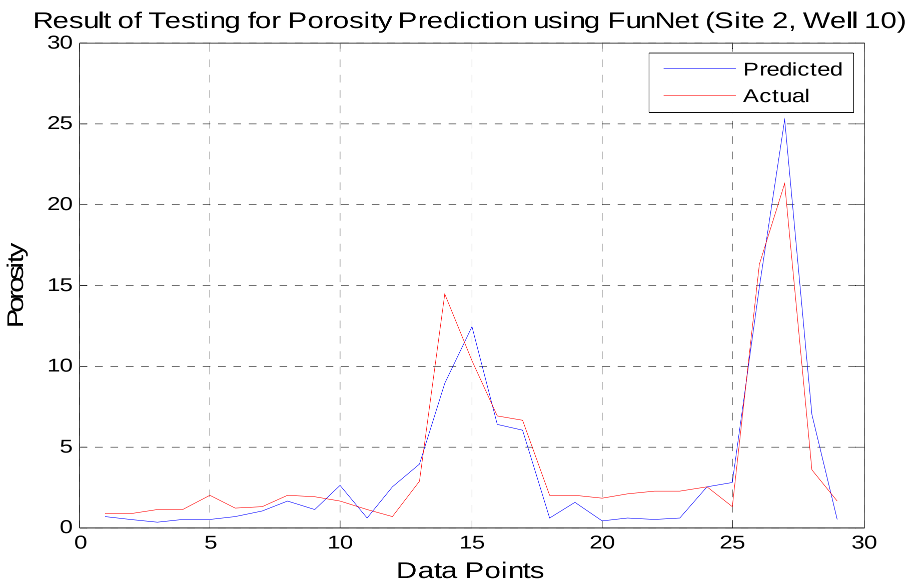

Figure 64: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FN Testing)

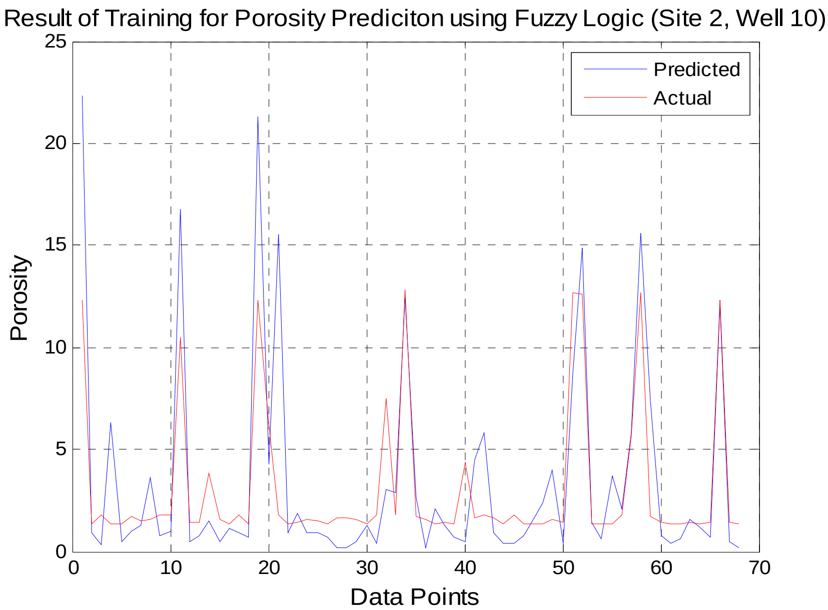

Figure 65: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FL Training)

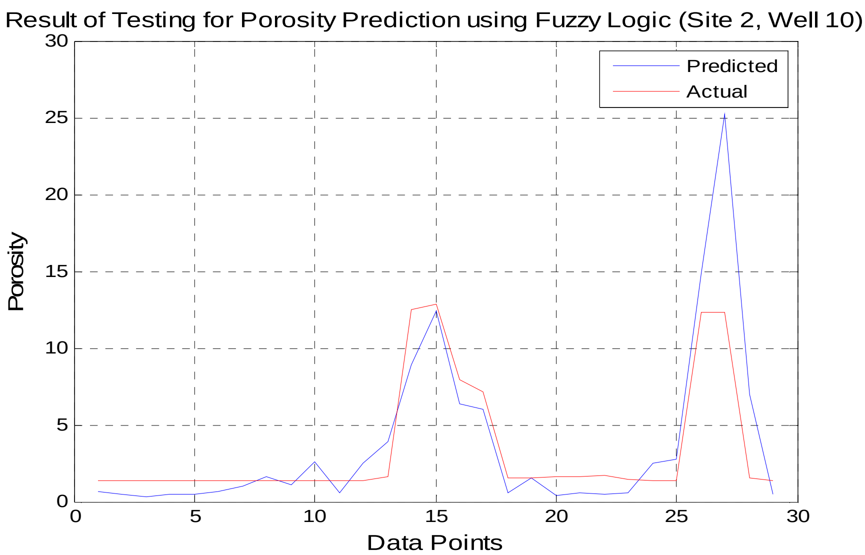

Figure 66: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FL Testing)

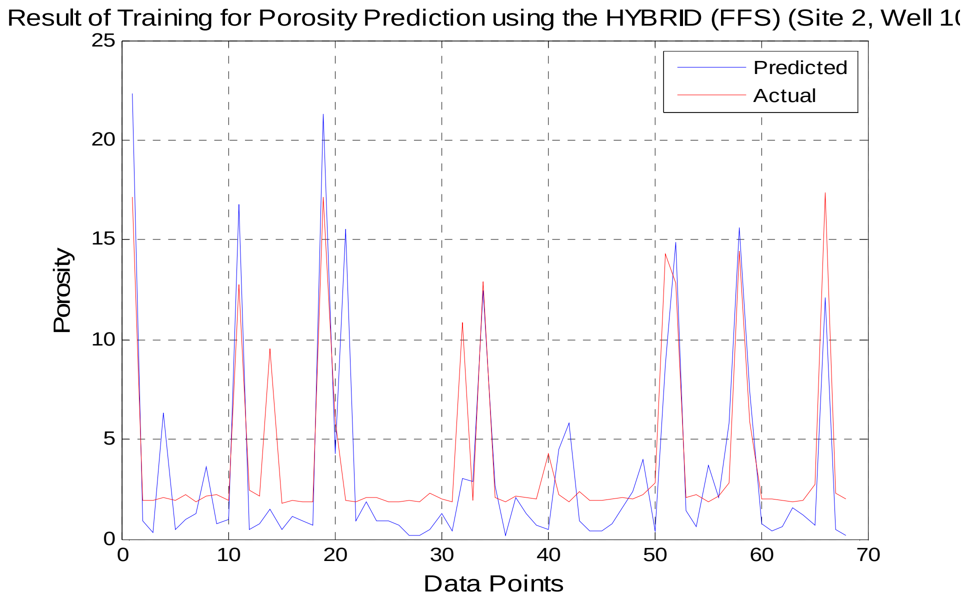

Figure 67: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FFS Training)

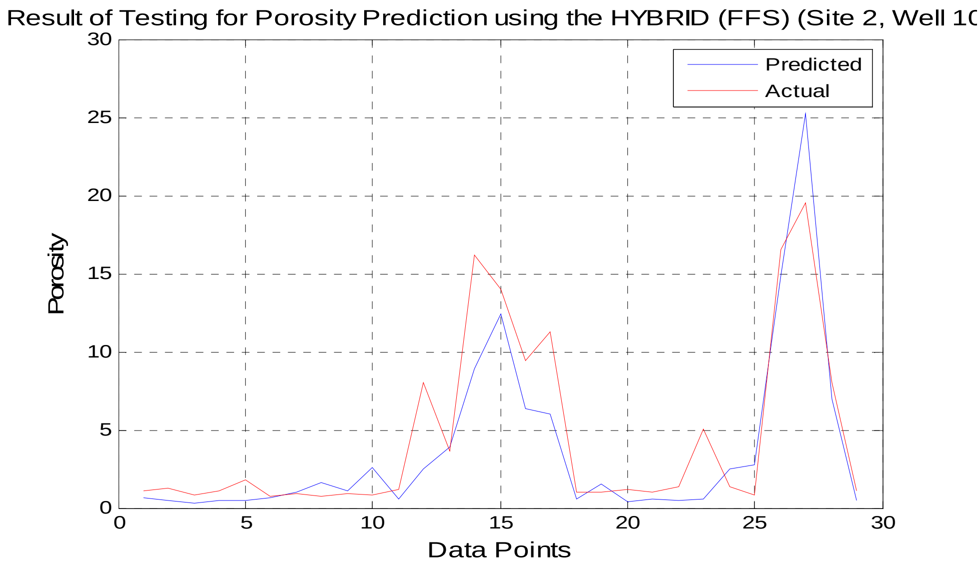

Figure 68: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FFS Testing)

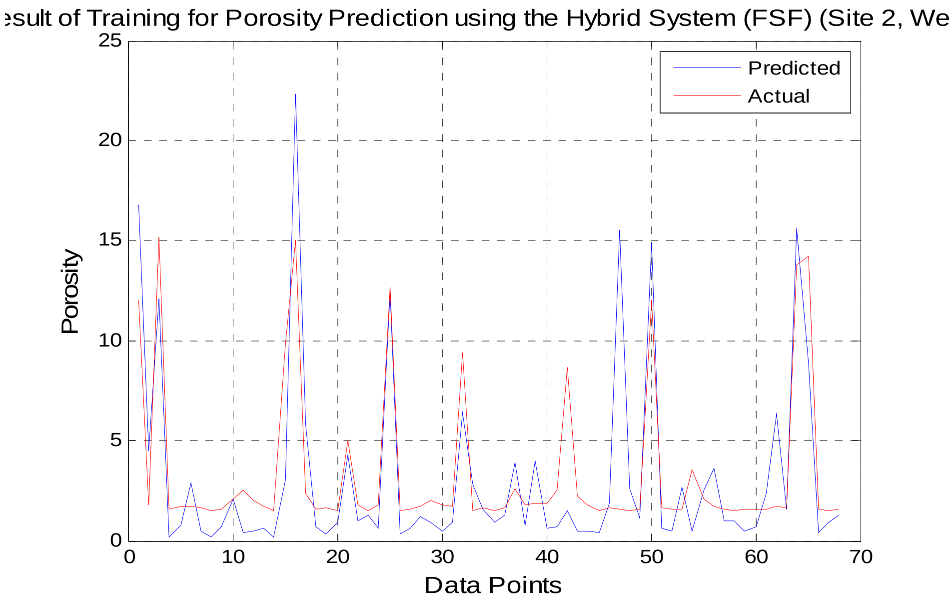

Figure 69: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FSF Training)

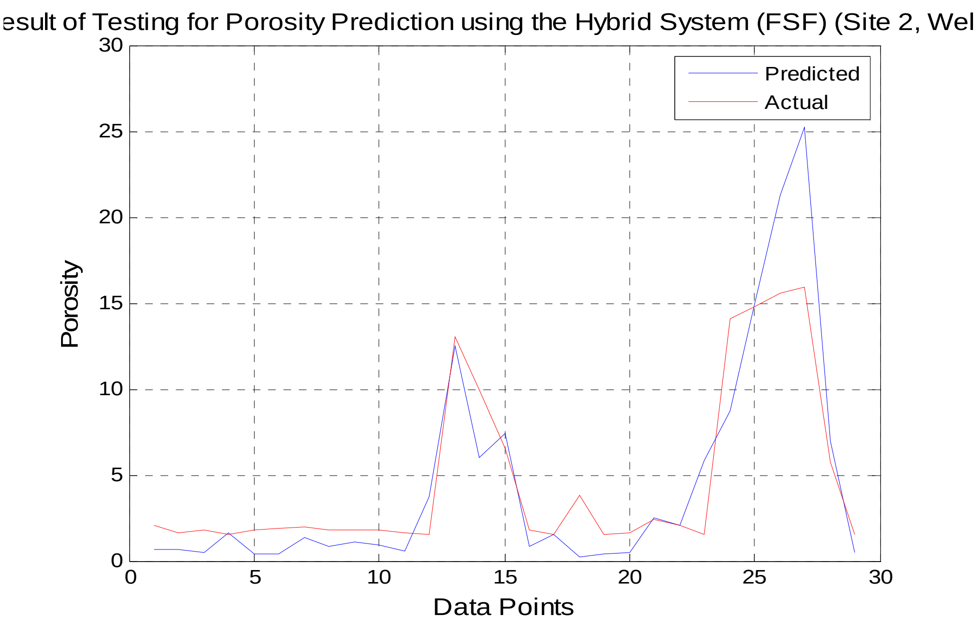

Figure 70: Plot of Actual vs. Predicted Porosity for Site 2, Well 10 (FSF Testing)

The comparative results of Correlation Coefficient and Execution Times are summarized in Figures 71 to 76.

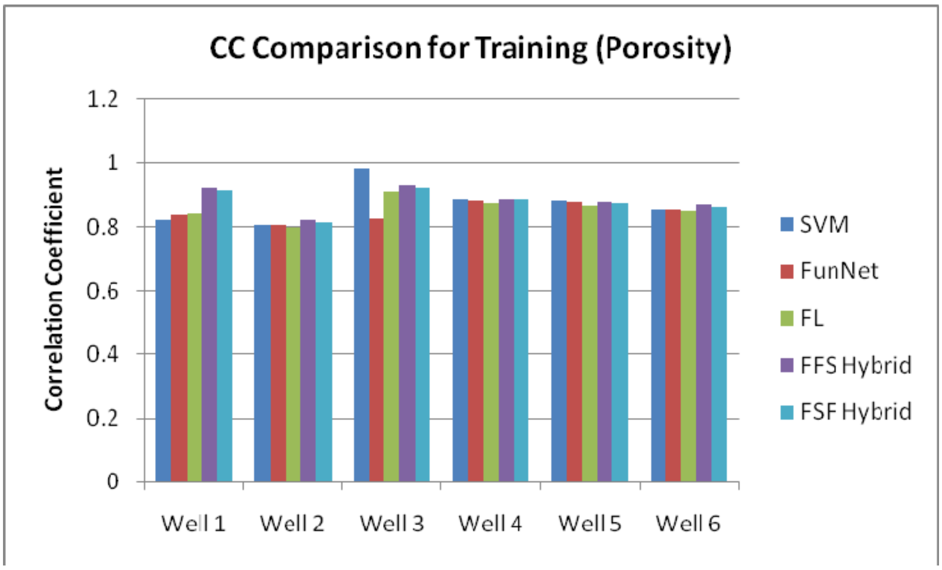

Figure 71: Correlation Coefficients comparisons for Porosity Training

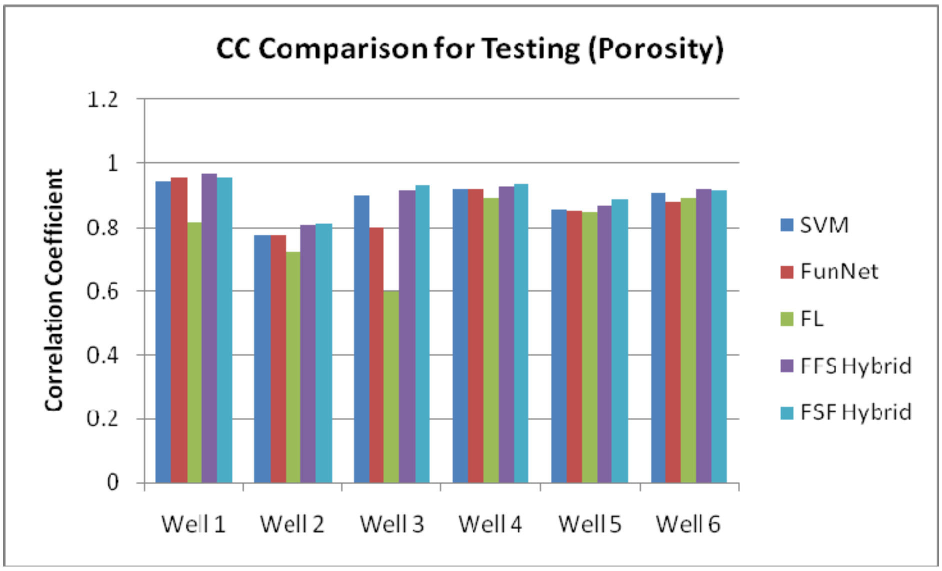

Figure 72: Correlation Coefficients comparisons for Porosity Testing

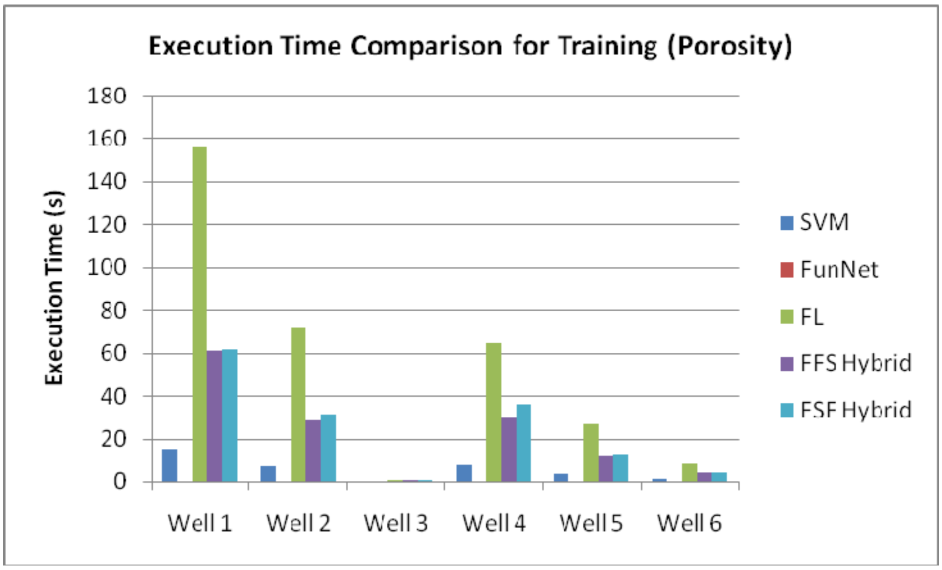

Figure 73: Execution Time comparisons for Porosity Training

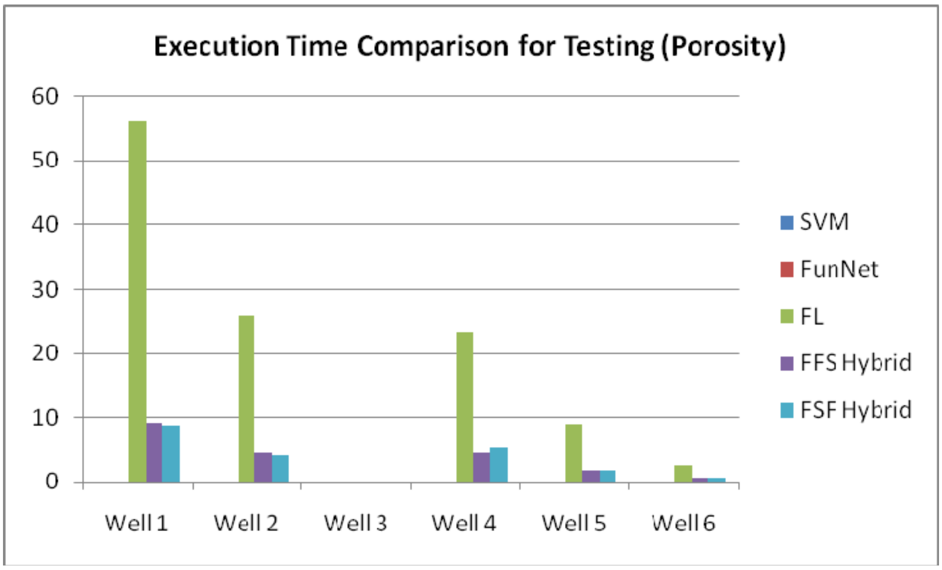

Figure 74: Execution Time comparisons for Porosity Testing

Figure 75: Execution Time comparisons for Porosity Training

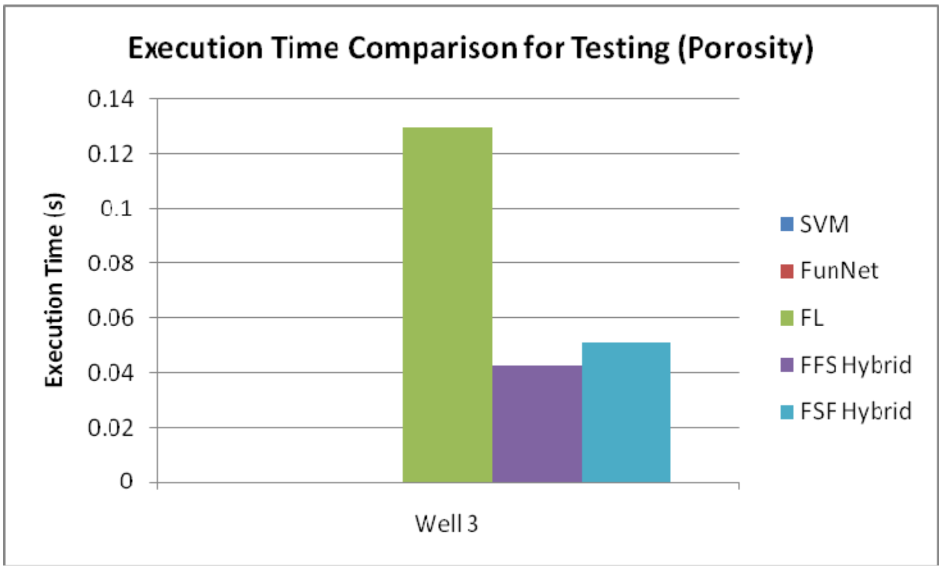

Figure 76: Execution Time comparisons for Porosity Testing

4.3 Results for the Prediction of Permeability

Similar to Porosity, table 23 – 27 present the results of the prediction of Permeability for the three wells in site 2, and the graphical plots of the actual and predicted outputs are presented in figures 77 – 126. The permeability outputs have been normalized by taking the natural logarithm.

Site 2, Well 1 (Permeability) – 355 Data Points – 247 for Training – 106 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Testing**	**Testing**	**Training**	**Testing**
SVM	**0.854109**	**0.832785**	**0.64724**	**0.68445**	**10.052083**	**0.000000**
FN	**0.852724**	**0.833204**	**0.64785**	**0.68113**	**0.140625**	**0.000000**
Fuzzy Logic	**0.869565**	**0.844982**	**0.62187**	**0.66946**	**187.494792**	**68.828125**
Hybrid – FFS	**0.872843**	**0.858610**	**1.10615**	**0.66580**	**43.333333**	**6.231250**
Hybrid – FSF	**0.827372**	**0.901920**	**0.72800**	**0.64289**	**44.630208**	**6.531250**

Table 23: Result of the Permeability prediction for Site 2, Well 1

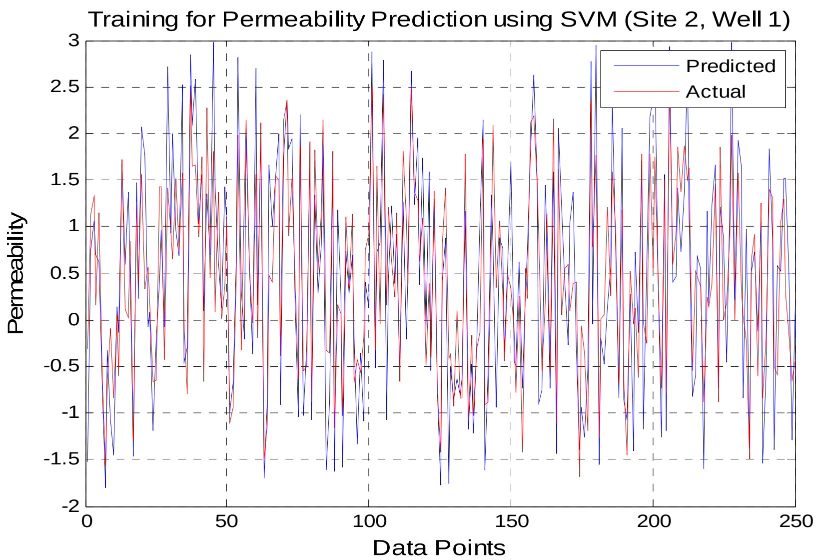

Figure 77: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (SVM Training)

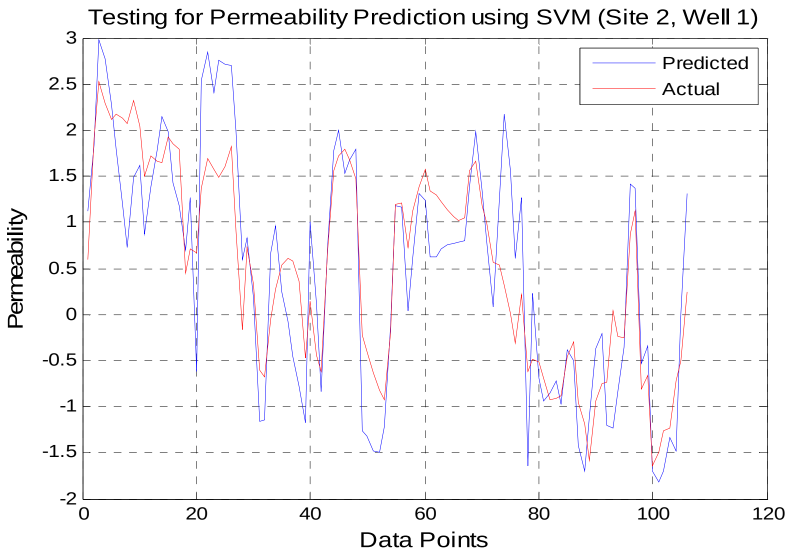

Figure 78: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (SVM Testing)

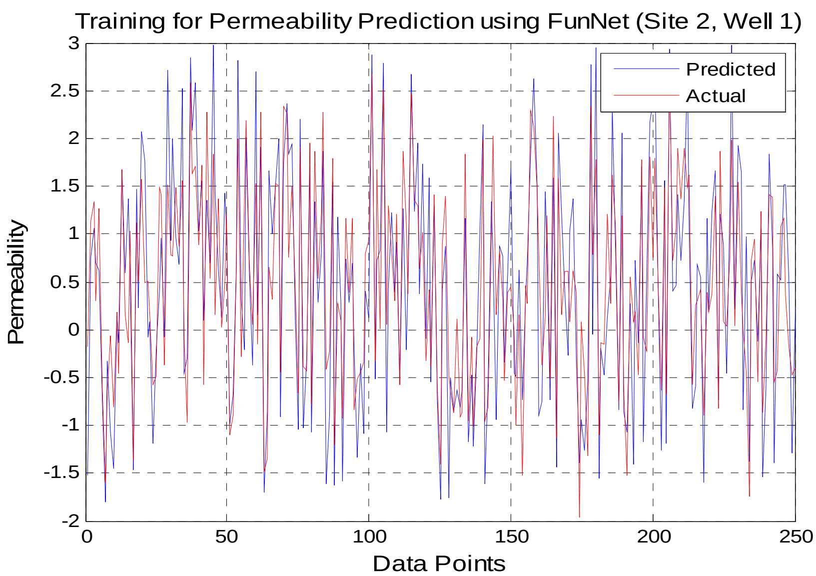

Figure 79: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (FN Training)

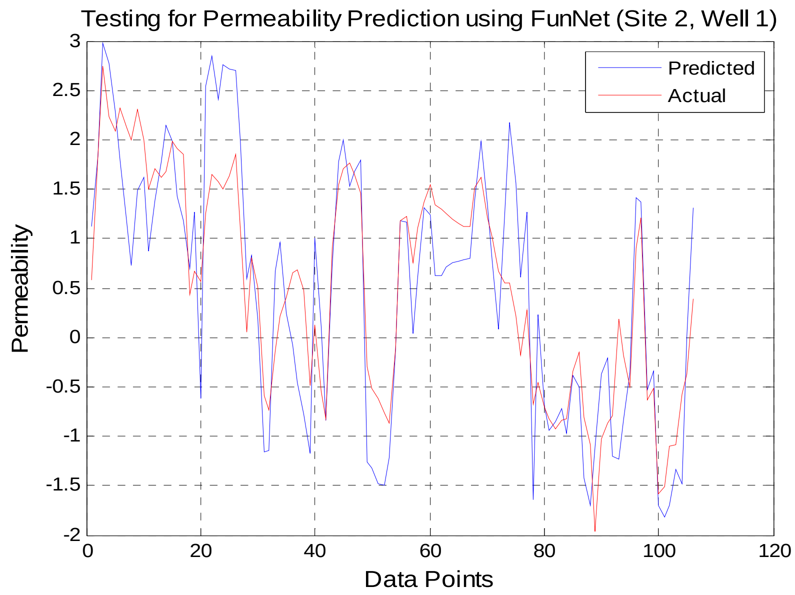

Figure 80: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (FN Testing)

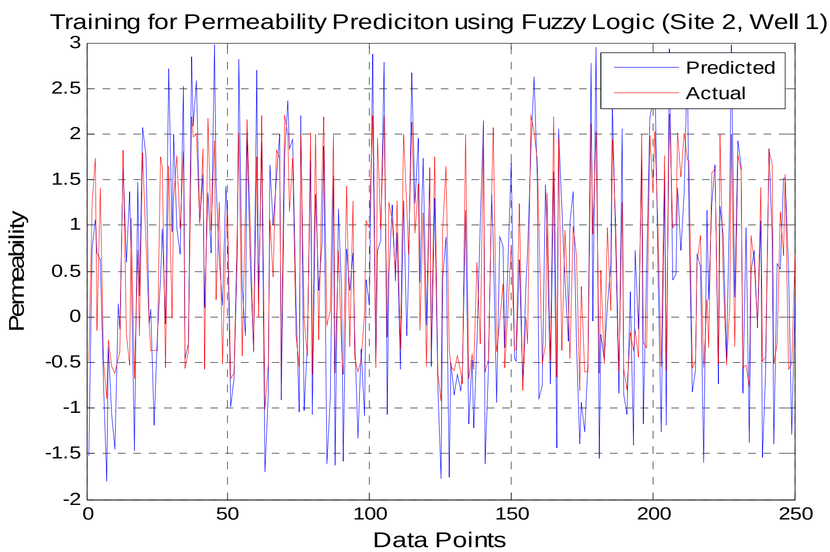

Figure 81: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (FL Training)

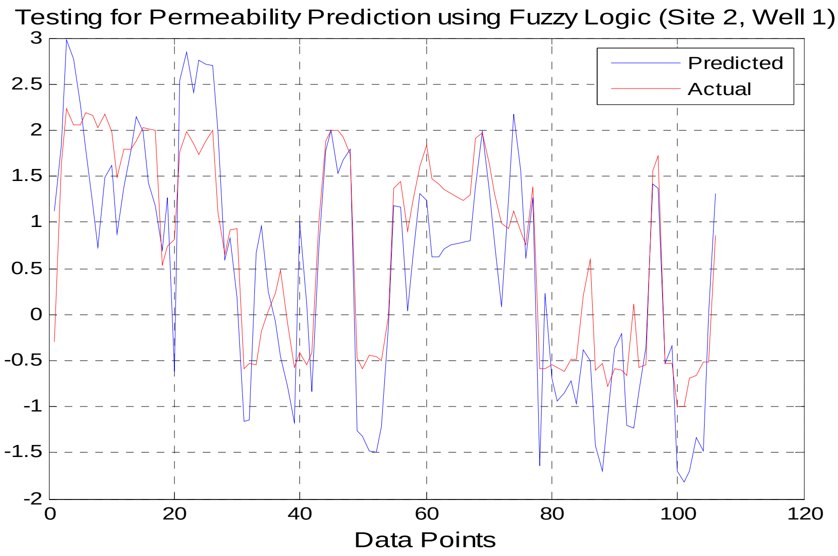

Figure 82: Plot of Actual vs. Predicted Permeability for Site 2, Well 1 (FL Testing)

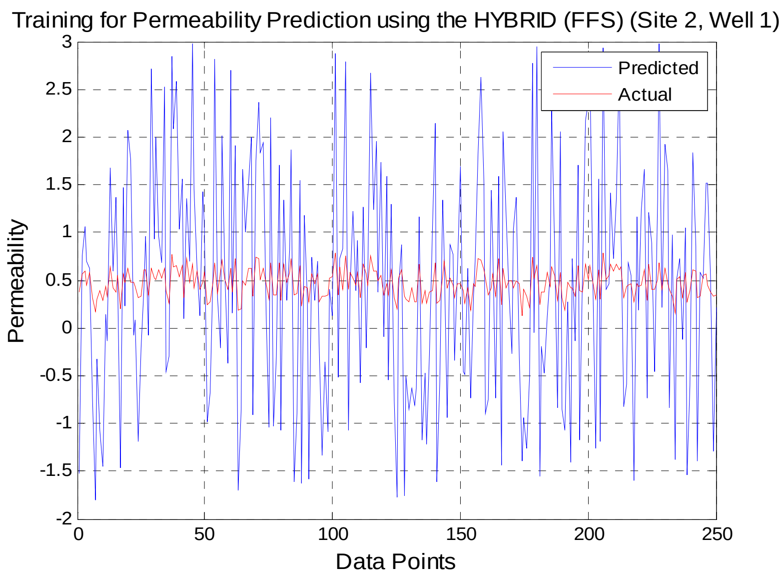

Figure 83: Actual vs. Predicted Permeability for Site 2, Well 1 (FFS Training)

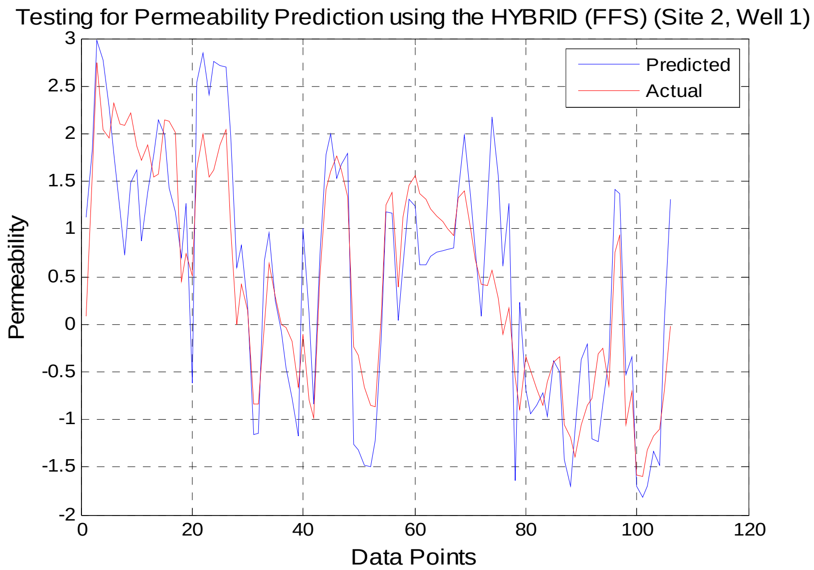

Figure 84: Actual vs. Predicted Permeability for Site 2, Well 1 (FFS Testing)

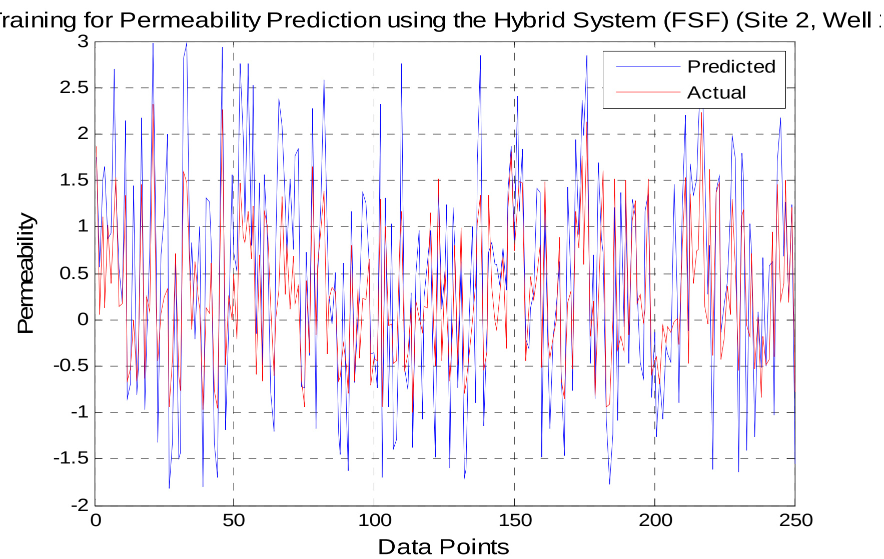

Figure 85: Actual vs. Predicted Permeability for Site 2, Well 1 (FSF Training)

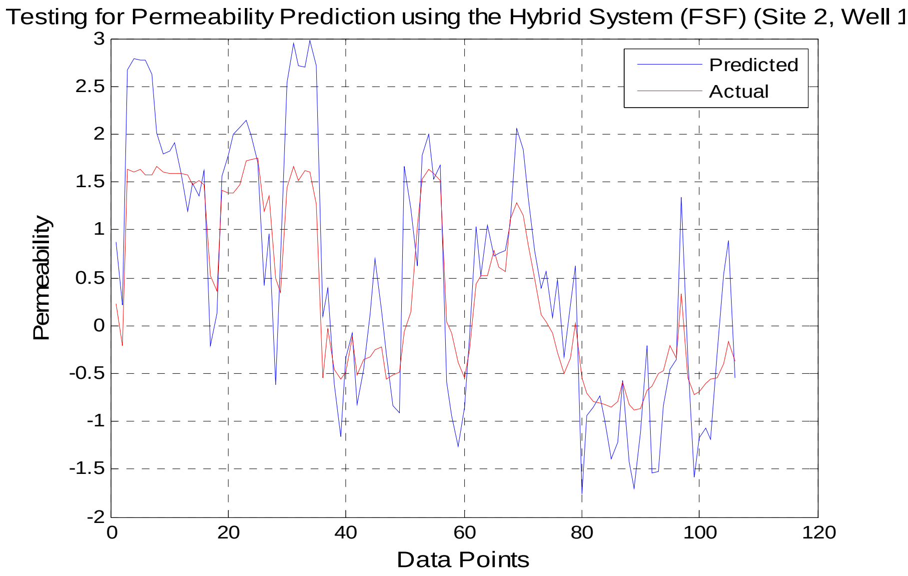

Figure 86: Actual vs. Predicted Permeability for Site 2, Well 1 (FSF Testing)

Site 2, Well 2 (Permeability) – 477 Data Points – 334 for Training – 143 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time (s)**	
	Training	**Testing**	**Testing**	**Testing**	**Training**	**Testing**
SVM	**0.864894**	**0.881033**	**0.63803**	**0.61685**	**18.661458**	**0.005208**
FN	**0.868102**	**0.877959**	**0.62799**	**0.62760**	**0.182292**	**0.000000**
Fuzzy Logic	**0.860039**	**0.866123**	**0.65863**	**0.67214**	**355.026042**	**128.739583**
Hybrid – FFS	**0.88142**	**0.895119**	**1.11178**	**0.60509**	**79.062500**	**12.463542**
Hybrid – FSF	**0.88144**	**0.903620**	**0.73102**	**0.72689**	**87.697917**	**14.140625**

Table 24: Result of the Permeability prediction for Site 2, Well 2

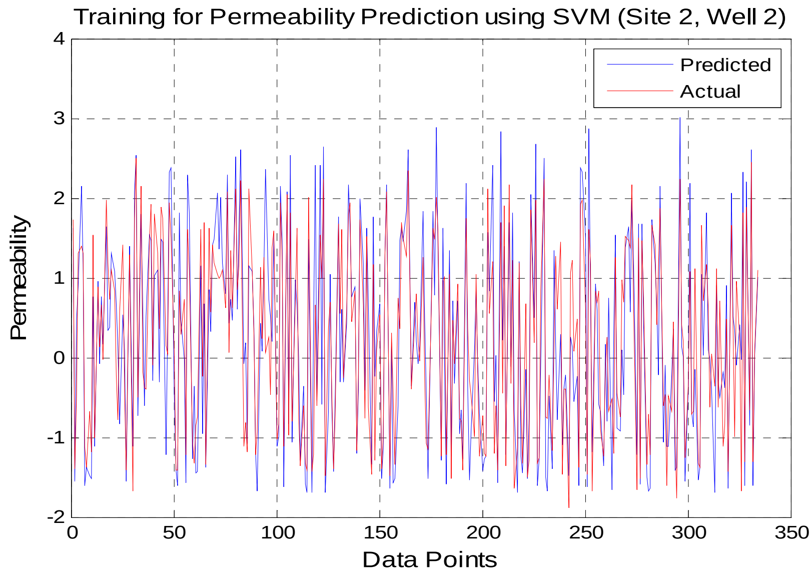

Figure 87: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (SVM Training)

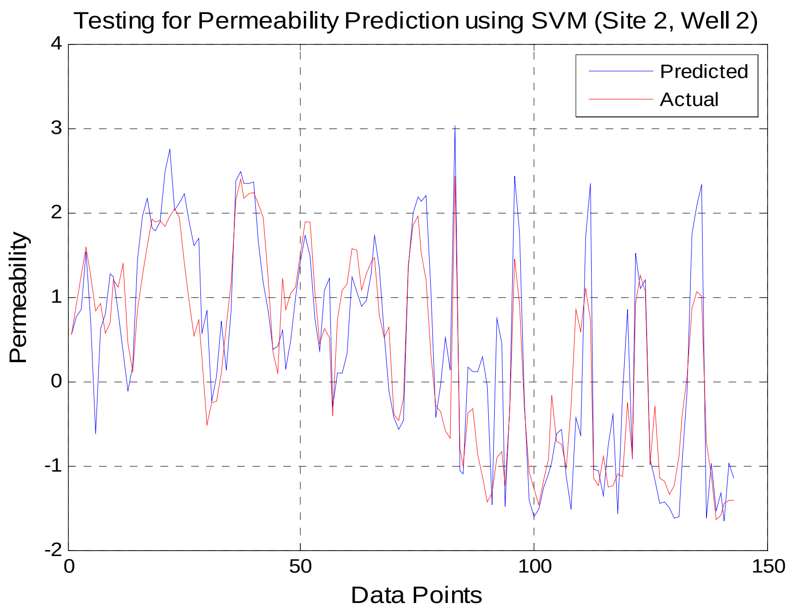

Figure 88: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (SVM Testing)

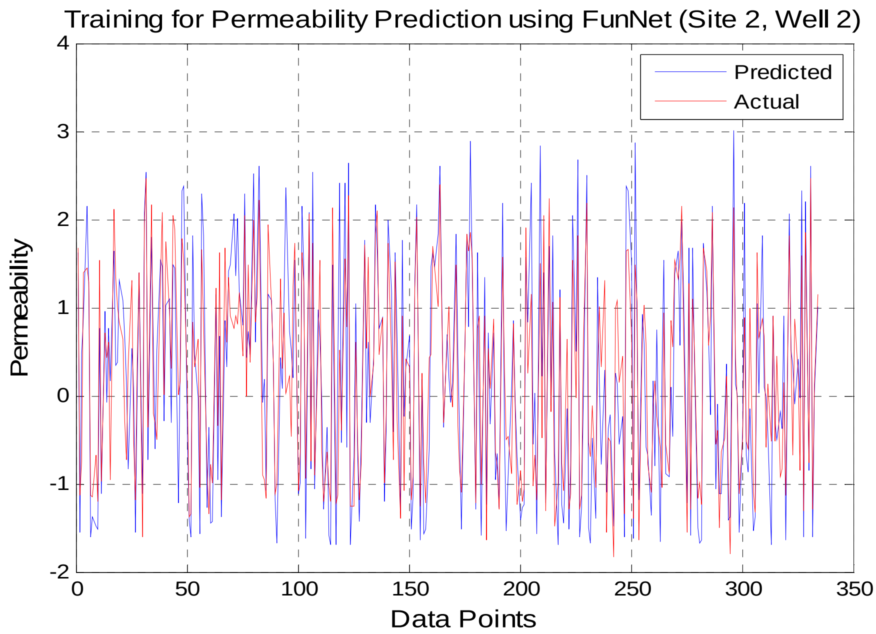

Figure 89: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (FN Training)

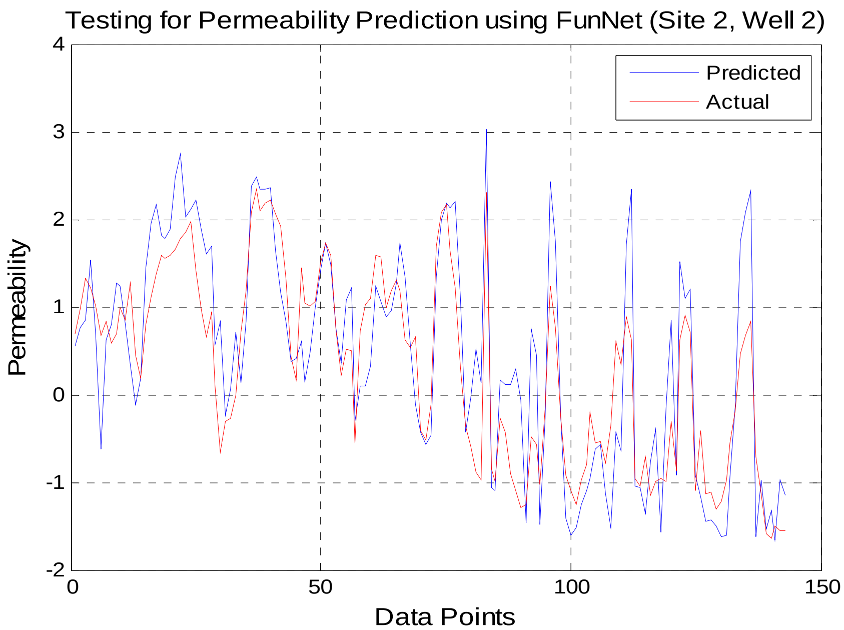

Figure 90: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (FN Testing)

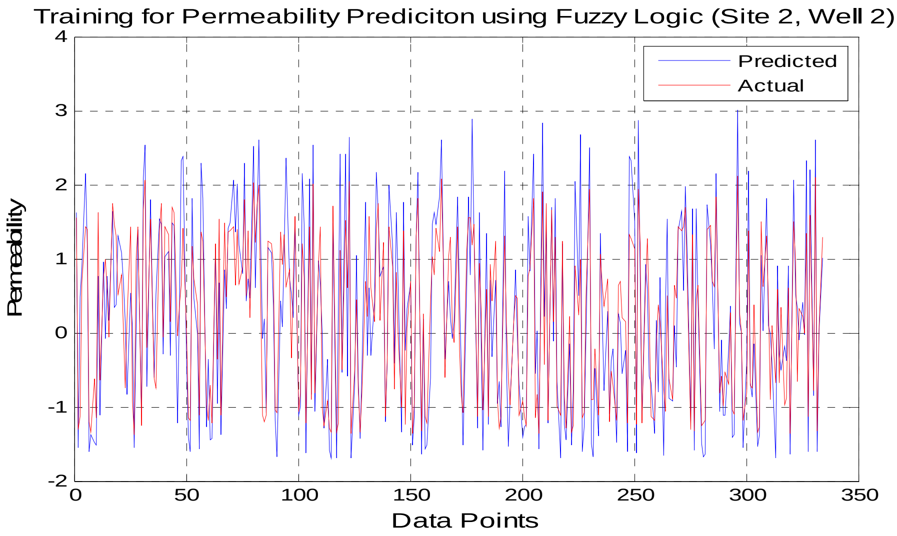

Figure 91: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (FL Training)

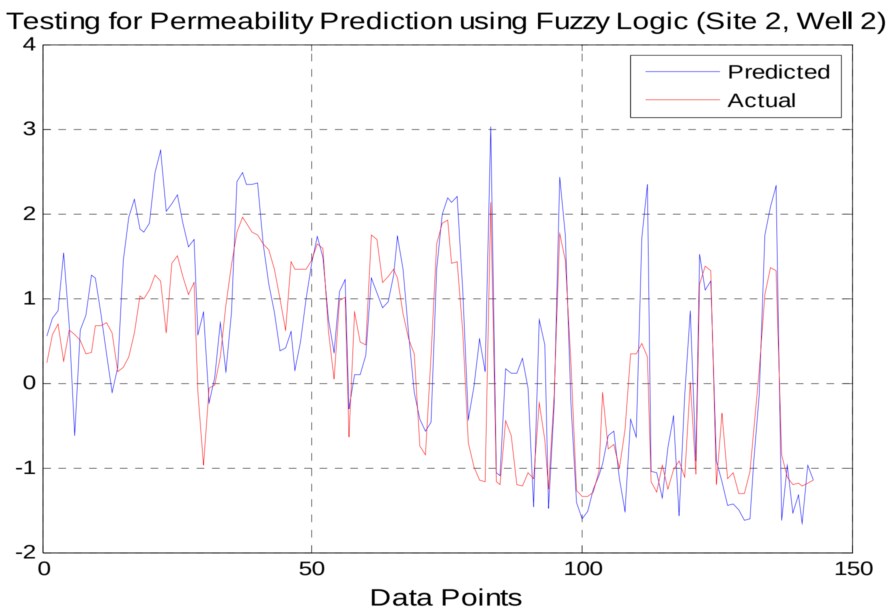

Figure 92: Plot of Actual vs. Predicted Permeability for Site 2, Well 2 (FL Testing)

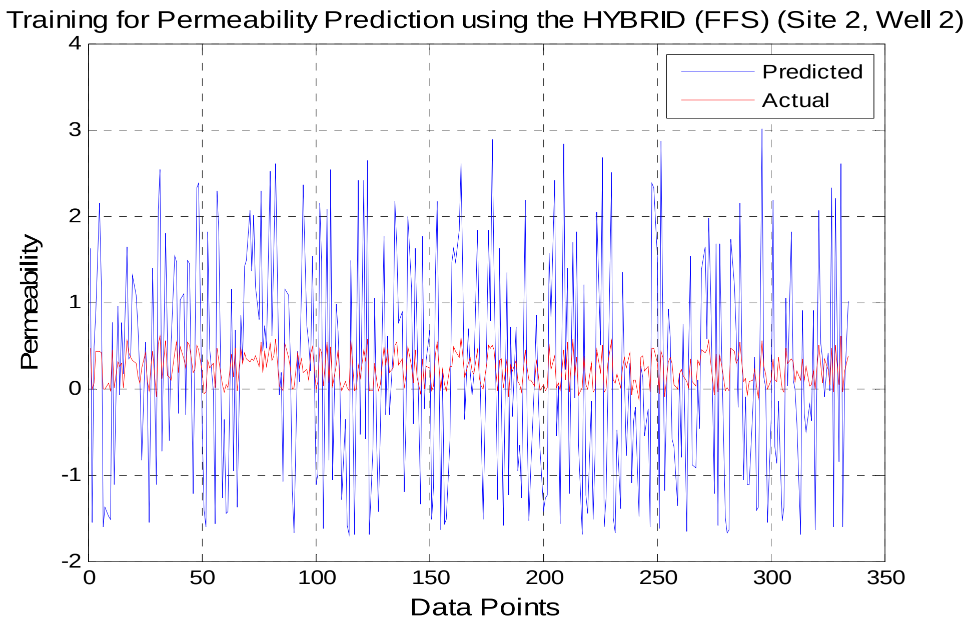

Figure 93: Actual vs. Predicted Permeability for Site 2, Well 2 (FFS Training)

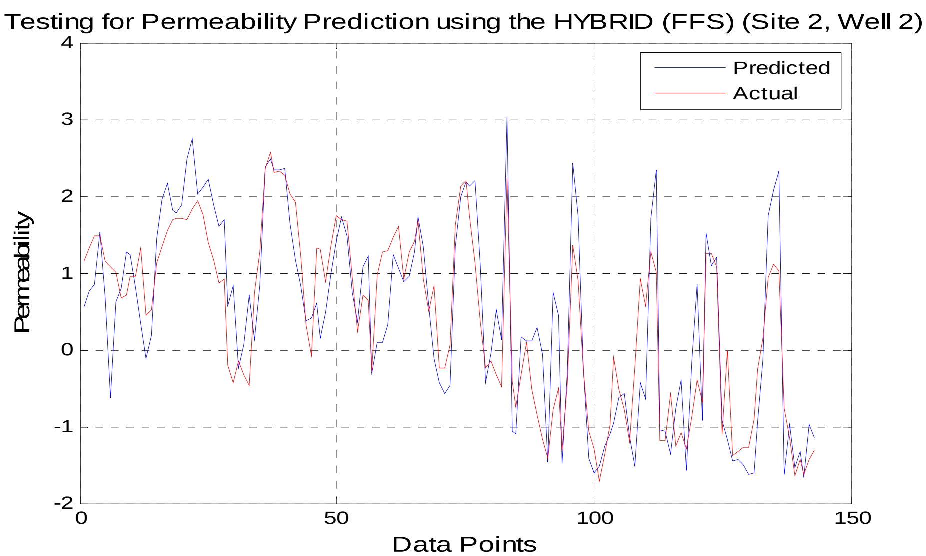

Figure 94: Actual vs. Predicted Permeability for Site 2, Well 2 (FFS Testing)

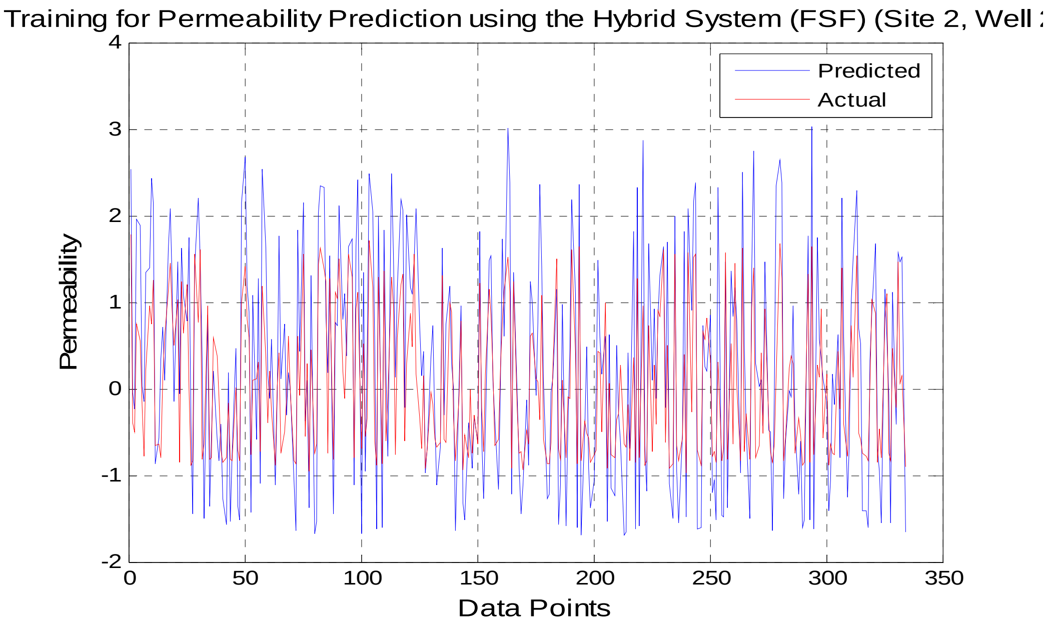

Figure 95: Actual vs. Predicted Permeability for Site 2, Well 2 (FSF Training)

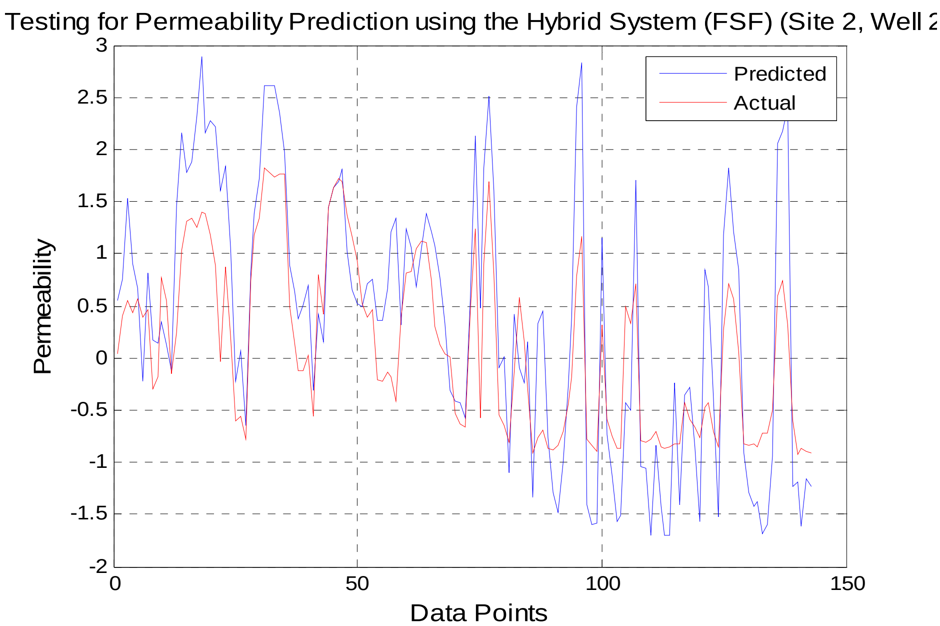

Figure 96: Actual vs. Predicted Permeability for Site 2, Well 2 (FSF Testing)

Site 2, Well 4 (Permeability) – 431 Data Points – 302 for Training – 129 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time(s)**	
	Training	**Testing**	**Testing**	**Testing**	**Training**	**Testing**
SVM	**0.812719**	**0.822752**	**0.79057**	**0.71183**	**18.255208**	**0.000000**
FN	**0.817004**	**0.831823**	**0.77165**	**0.69502**	**0.140625**	**0.000000**
Fuzzy Logic	**0.759445**	**0.760171**	**0.93977**	**0.88106**	**304.005208**	**111.661458**
Hybrid – FFS	**0.817269**	**0.843163**	**1.20859**	**0.67158**	**64.505208**	**10.098958**
Hybrid – FSF	**0.802654**	**0.847340**	**0.85279**	**0.84433**	**66.572917**	**10.015625**

Table 25: Result of the Permeability prediction for Site 2, Well 4

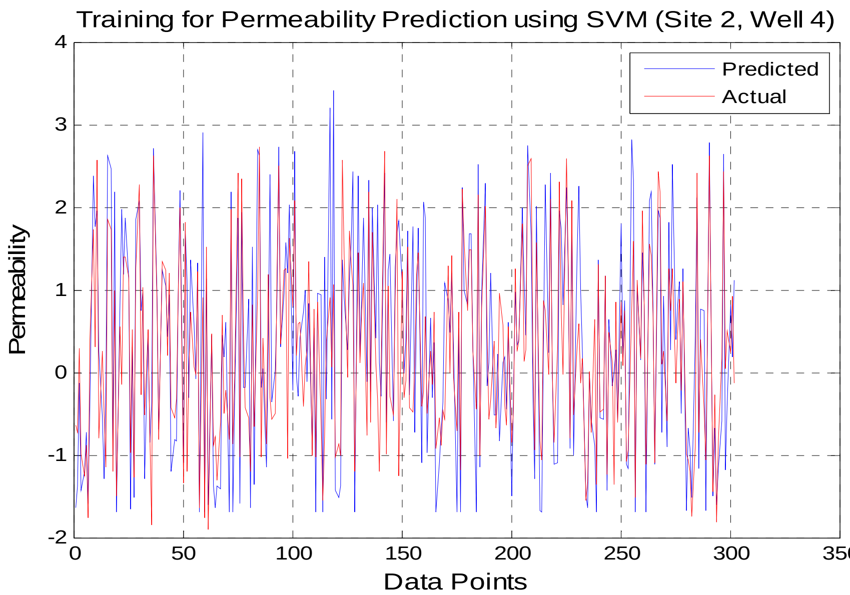

Figure 97: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (SVM Training)

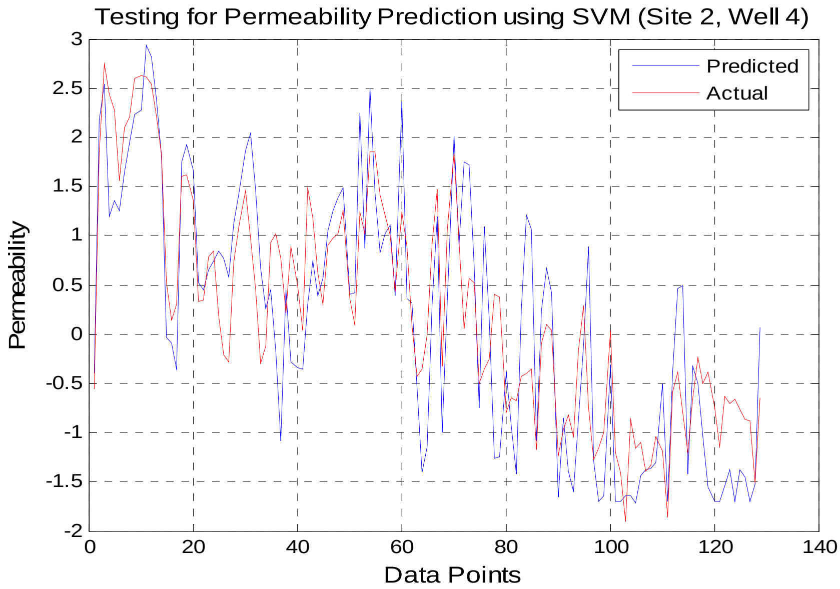

Figure 98: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (SVM Testing)

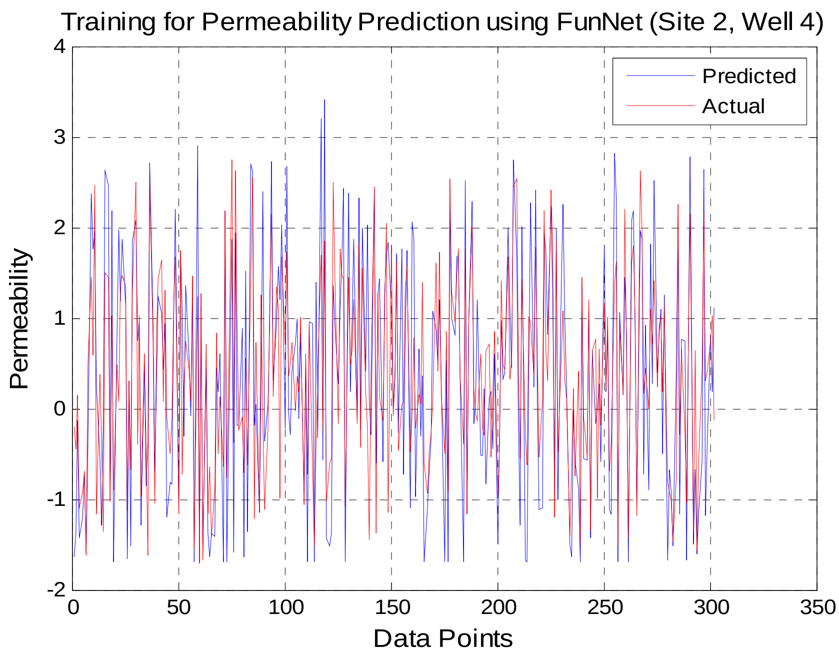

Figure 99: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (FN Training)

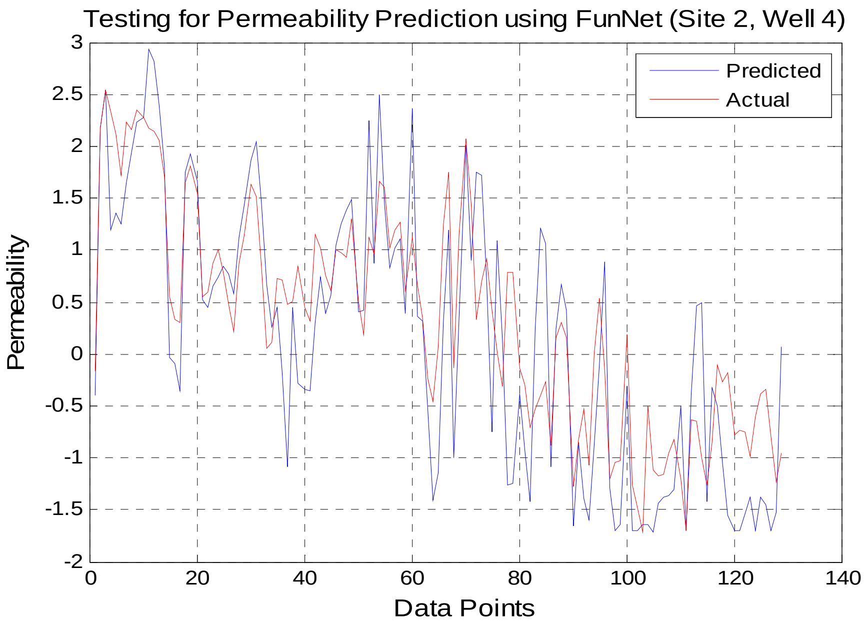

Figure 100: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (FN Testing)

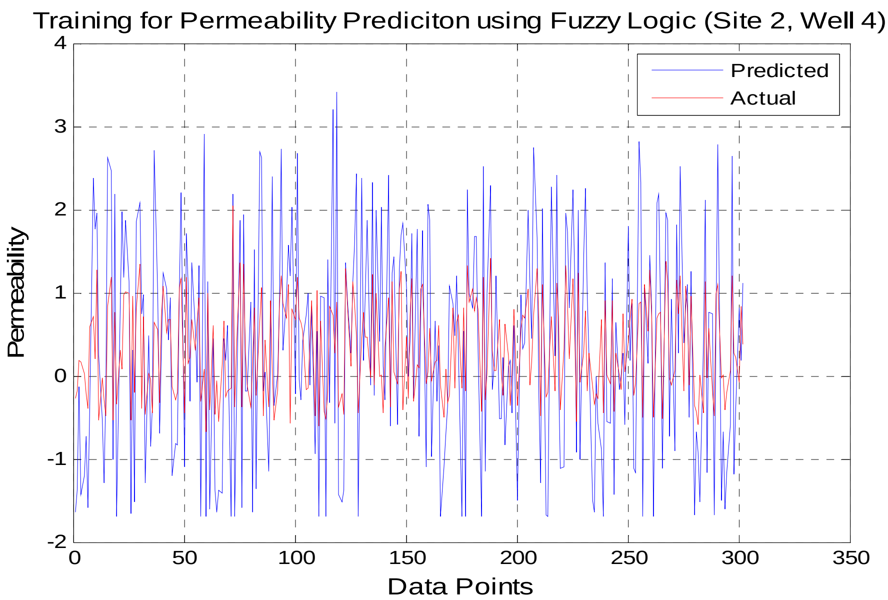

Figure 101: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (FL Training)

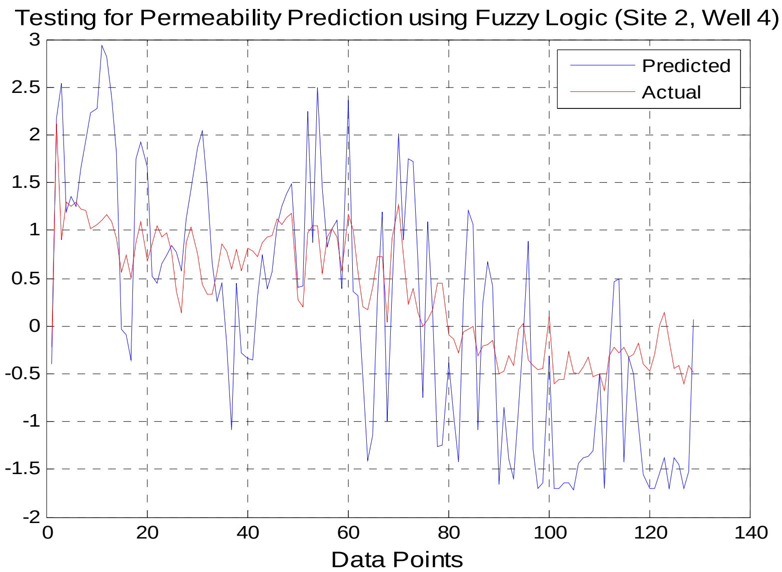

Figure 102: Plot of Actual vs. Predicted Permeability for Site 2, Well 4 (FL Testing)

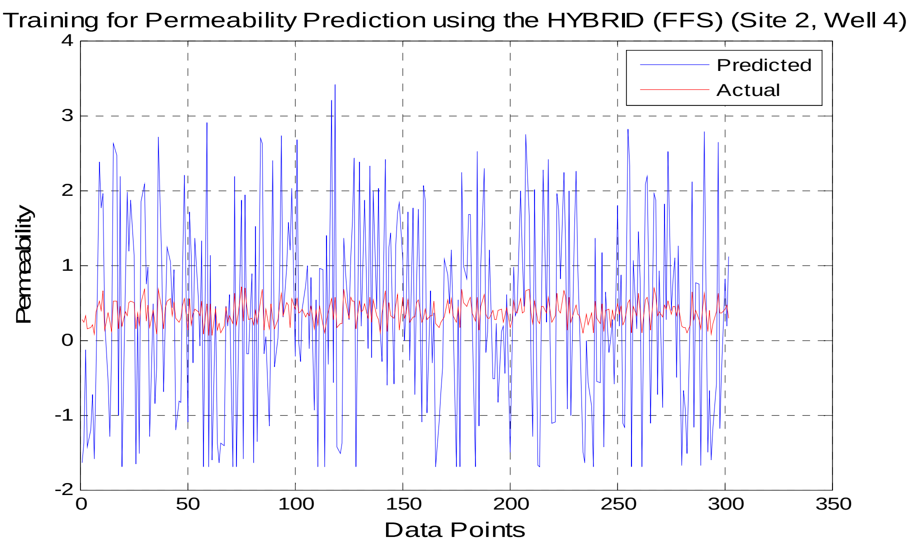

Figure 103: Actual vs. Predicted Permeability for Site 2, Well 4 (FFS Training)

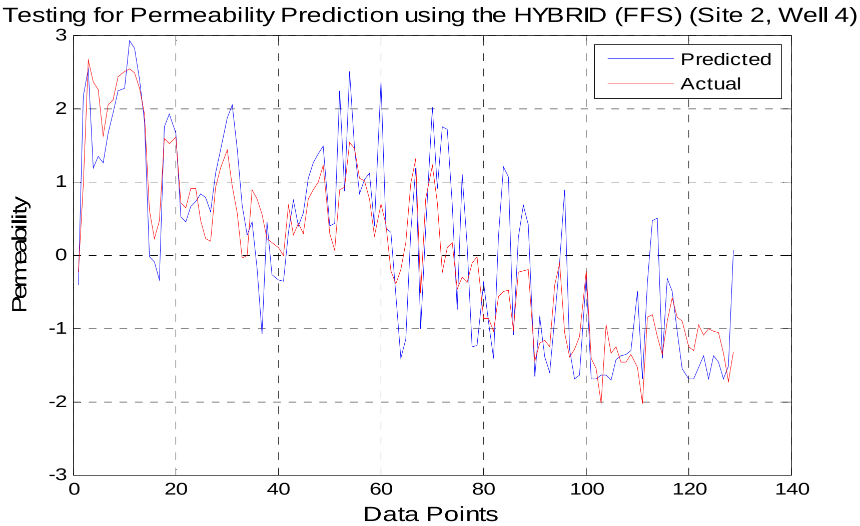

Figure 104: Actual vs. Predicted Permeability for Site 2, Well 4 (FFS Testing)

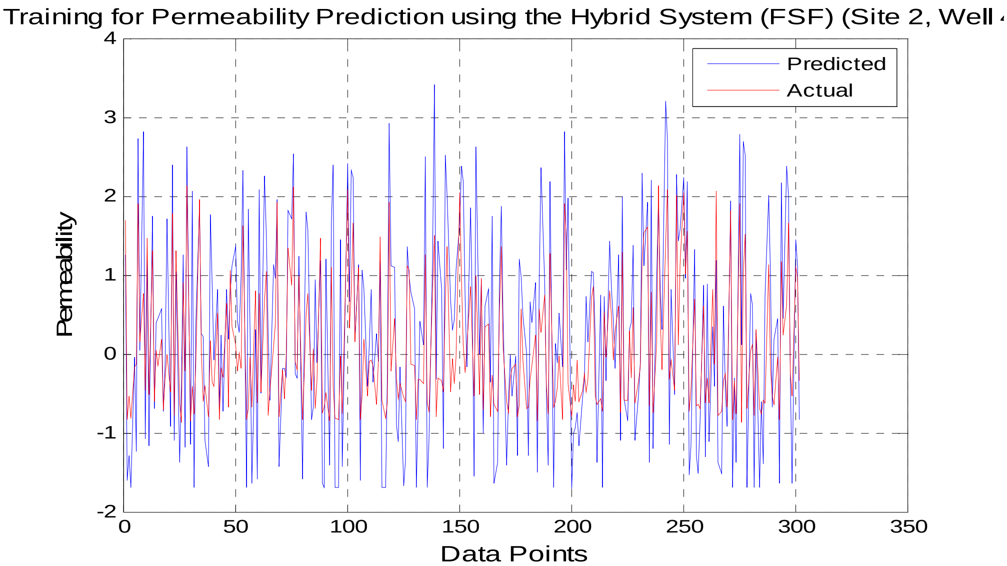

Figure 105: Actual vs. Predicted Permeability for Site 2, Well 4 (FSF Training)

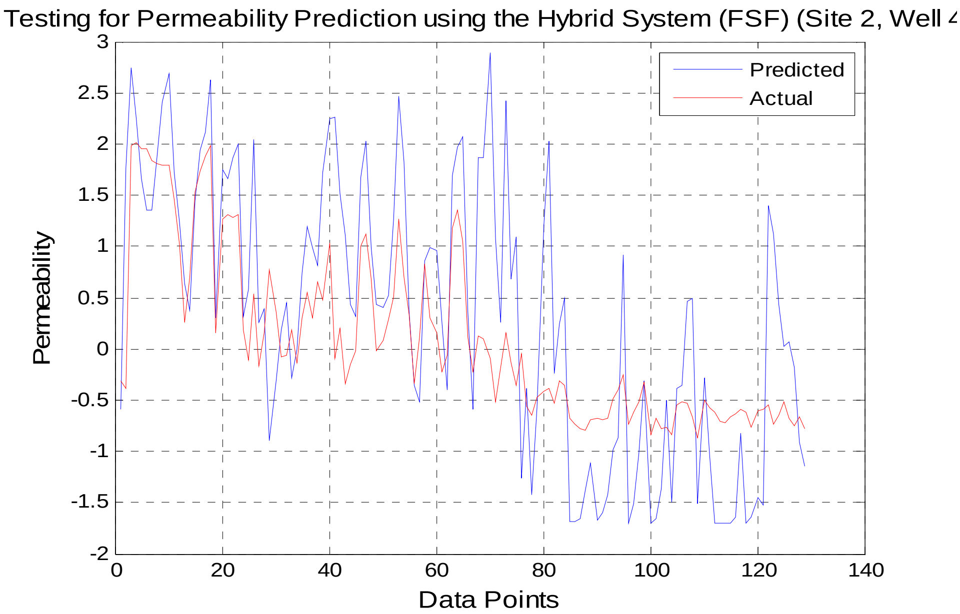

Figure 106: Actual vs. Predicted Permeability for Site 2, Well 4 (FSF Testing)

Site 2, Well 6 (Permeability) – 387 Data Points – 271 for Training – 116 for Testing						
Model	**Correlation Coefficient**		**RMSE**		**Execution Time(s)**	
	Training	**Testing**	**Testing**	**Testing**	**Training**	**Testing**
SVM	**0.821267**	**0.781080**	**0.66644**	**0.74348**	**14.401042**	**0.005208**
FN	**0.823928**	**0.806852**	**0.66074**	**0.69975**	**0.140625**	**0.000000**
Fuzzy Logic	**0.865726**	**0.828990**	**0.64096**	**0.63275**	**260.875**	**95.328125**
Hybrid – FFS	**0.824454**	**0.824671**	**1.07297**	**0.66281**	**49.973958**	**7.833333**
Hybrid – FSF	**0.808248**	**0.824798**	**0.69798**	**0.70107**	**49.541667**	**7.671875**

Table 26: Result of the Permeability prediction for Site 2, Well 6

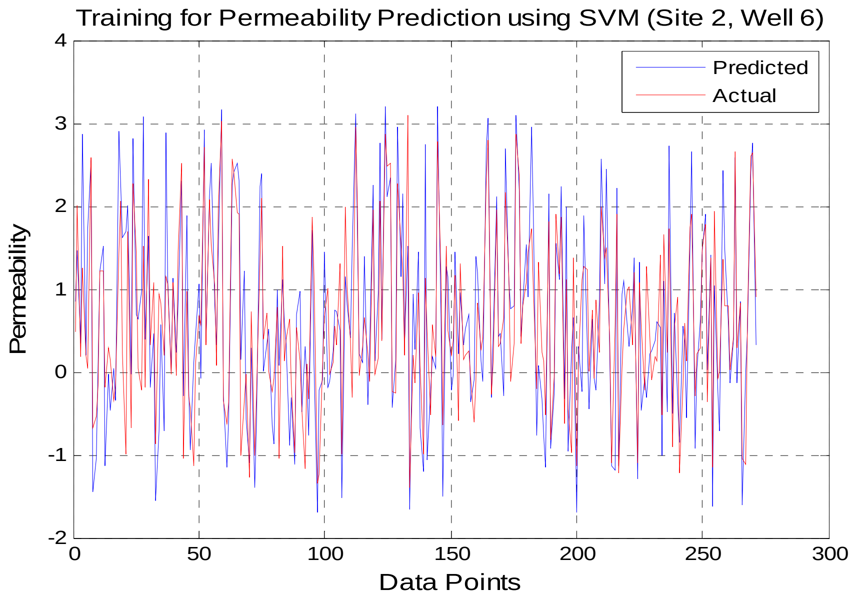

Figure 107: Plot of Actual/Predicted Permeability for Site 2, Well 6 (SVM Training)

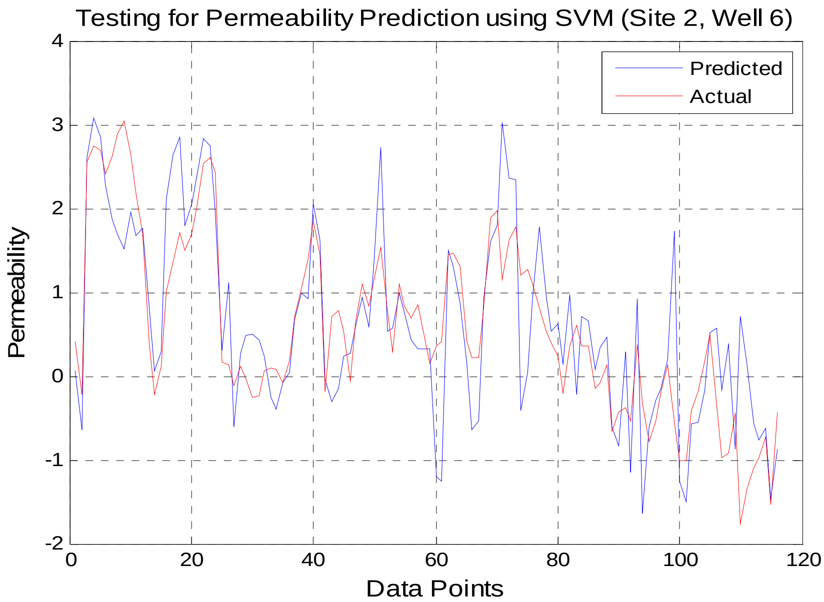

Figure 108: Plot of Actual vs. Predicted Permeability for Site 2, Well 6 (SVM Testing)

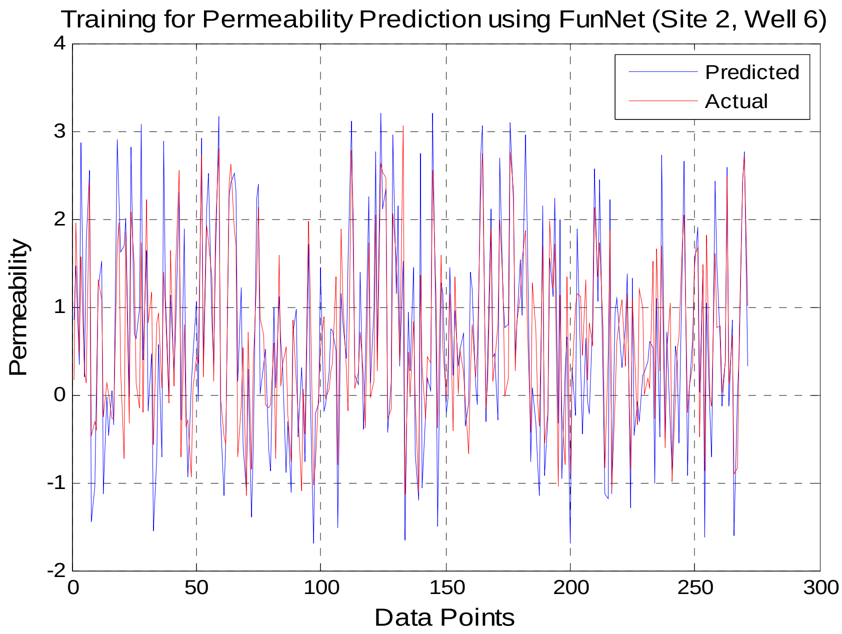

Figure 109: Plot of Actual vs. Predicted Permeability for Site 2, Well 6 (FN Training)

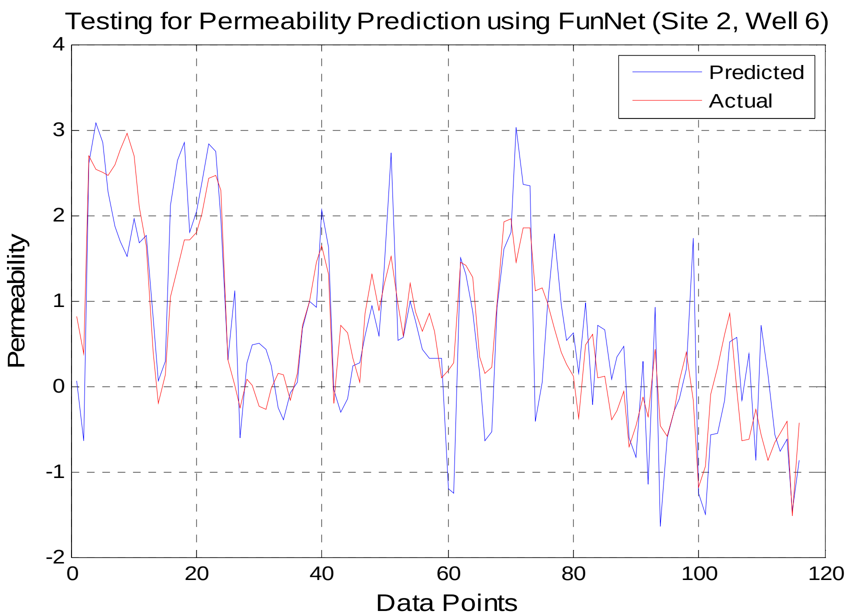

Figure 110: Plot of Actual vs. Predicted Permeability for Site 2, Well 6 (FN Testing)

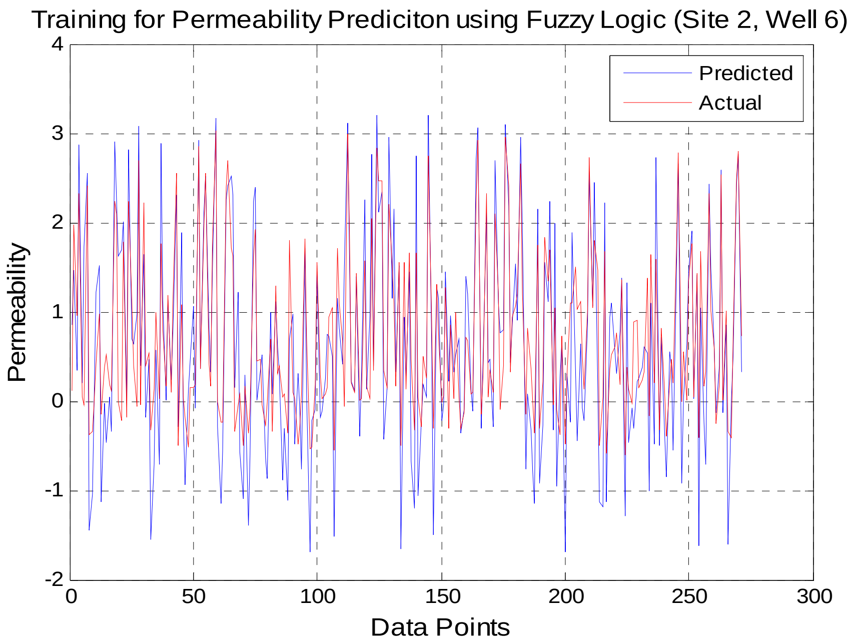

Figure 111: Plot of Actual vs. Predicted Permeability for Site 2, Well 6 (FL Training)

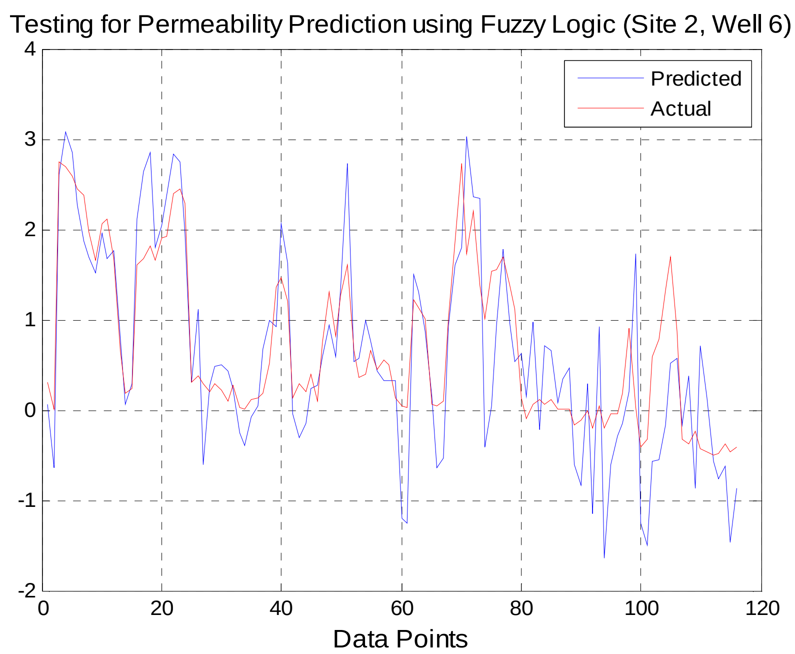

Figure 112: Plot of Actual vs. Predicted Permeability for Site 2, Well 6 (FL Testing)

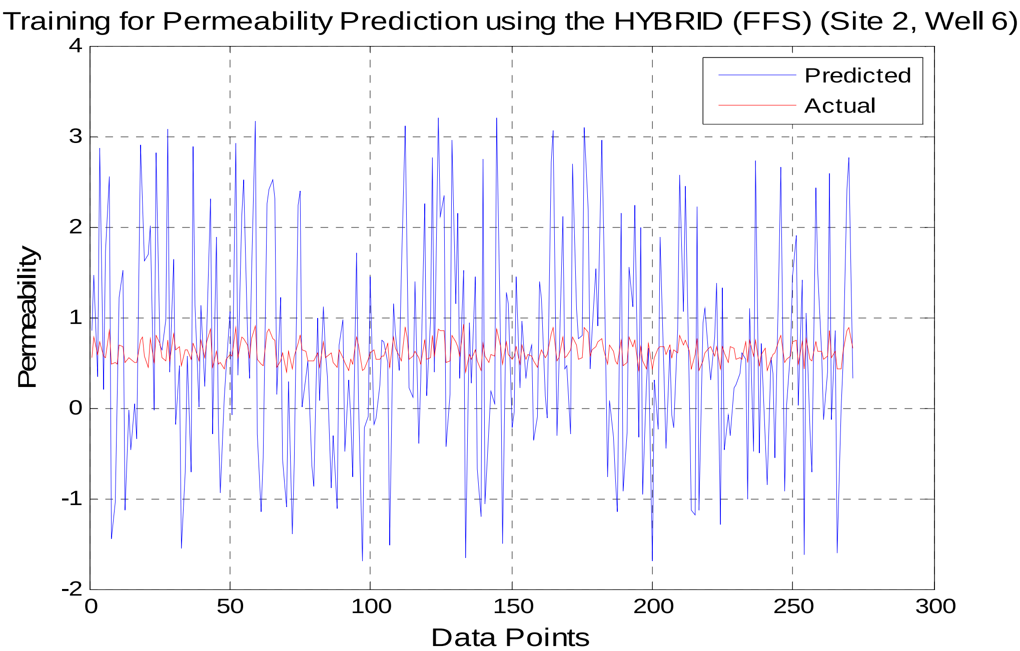

Figure 113: Actual vs. Predicted Permeability for Site 2, Well 6 (FFS Training)

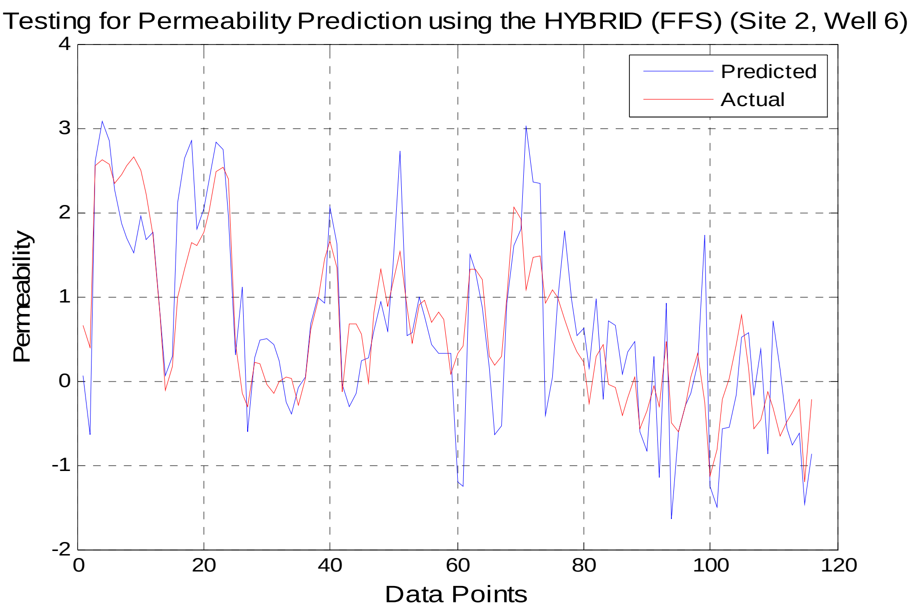

Figure 114: Actual vs. Predicted Permeability for Site 2, Well 6 (FFS Testing)

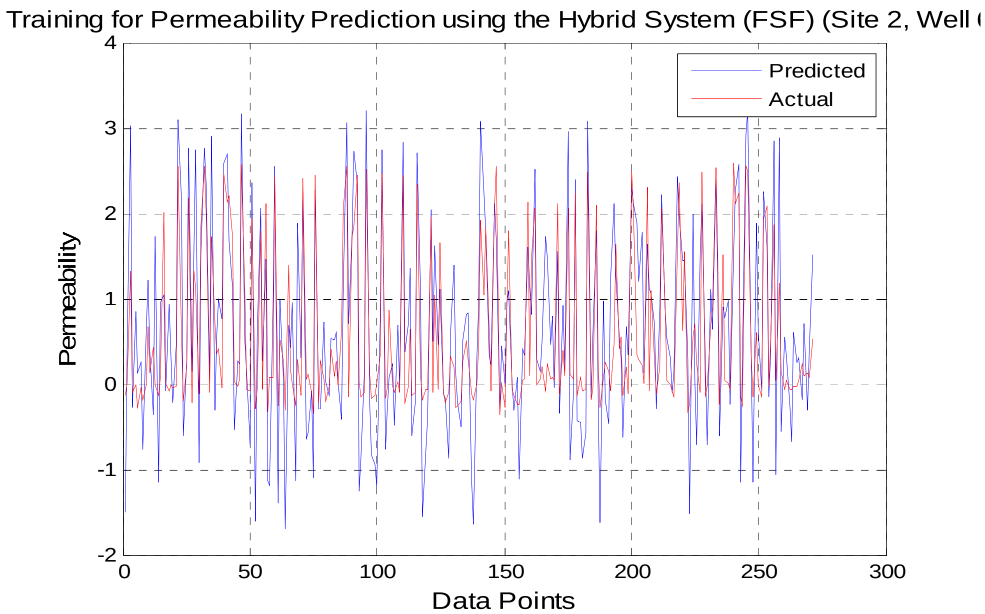

Figure 115: Actual vs. Predicted Permeability for Site 2, Well 6 (FSF Training)

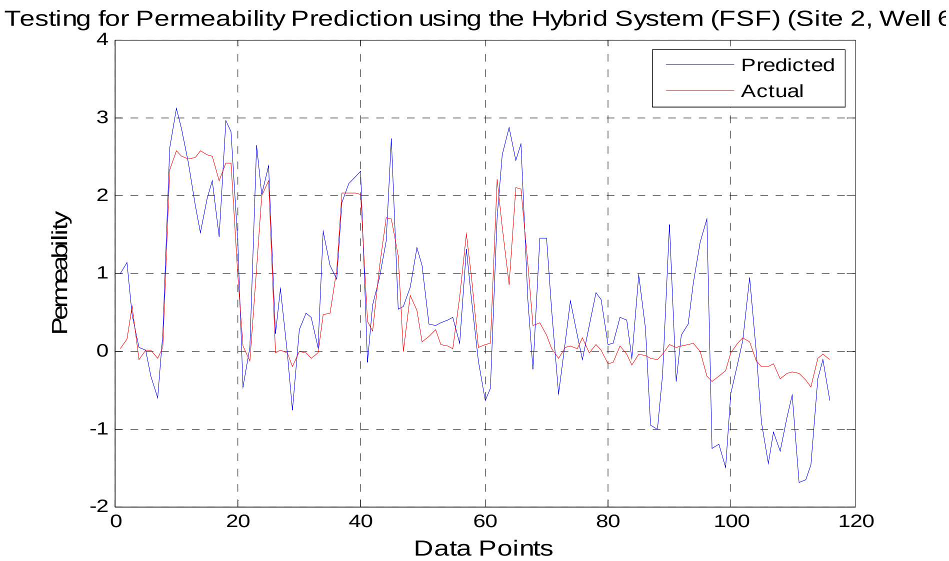

Figure 116: Actual vs. Predicted Permeability for Site 2, Well 6 (FSF Testing)

Site 2, Well 7 (Permeability) – 40 Data Points – 28 for Training – 12 for Testing						
Model	Correlation Coefficient		RMSE		Execution Time	
	Training	Testing	Testing	Testing	Training	Testing
SVM	0.896306	0.714189	0.53969	1.00971	0.487500	0.000000
FN	0.905097	0.669544	0.53419	0.92967	0.089063	0.000000
Fuzzy Logic	0.915091	0.681800	0.48686	0.91266	3.021875	1.195313
Hybrid – FFS	0.905626	0.999860	1.04798	0.08387	0.959375	0.112500
Hybrid – FSF	0.928527	0.974989	0.49677	0.48307	2.171875	0.239844

Table 27: Result of the Permeability prediction for Site 2, Well 7

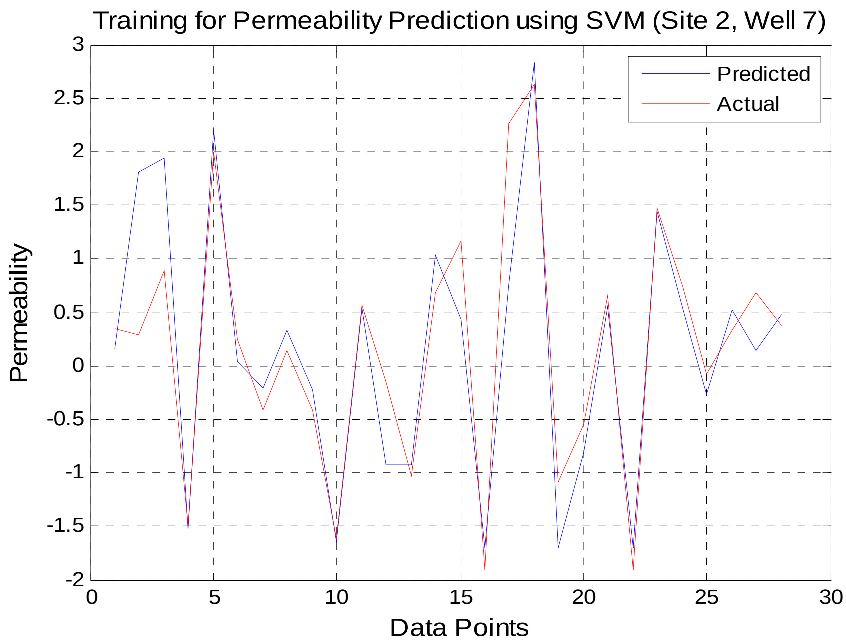

Figure 117 Plot of Actual/Predicted Permeability for Site 2, Well 7 (SVM Training)

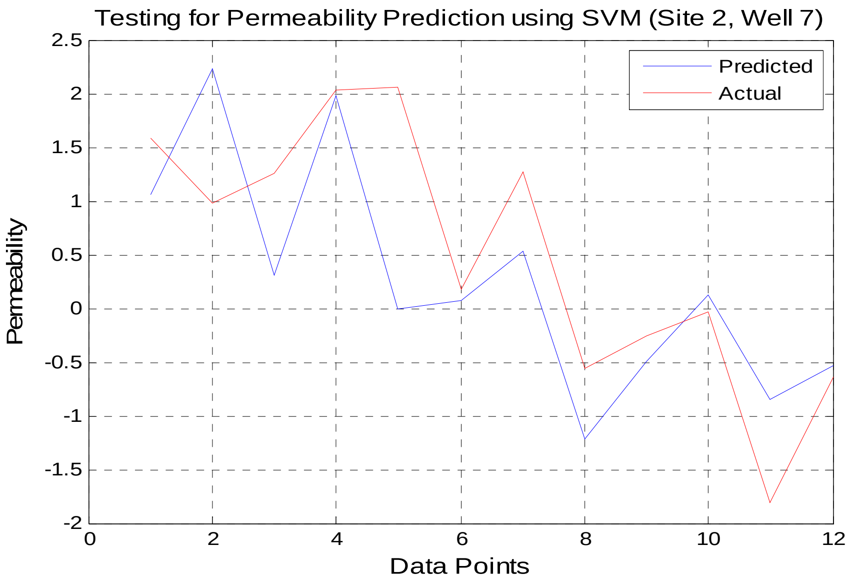

Figure 118: Plot of Actual vs. Predicted Permeability for Site 2, Well 7 (SVM Testing)

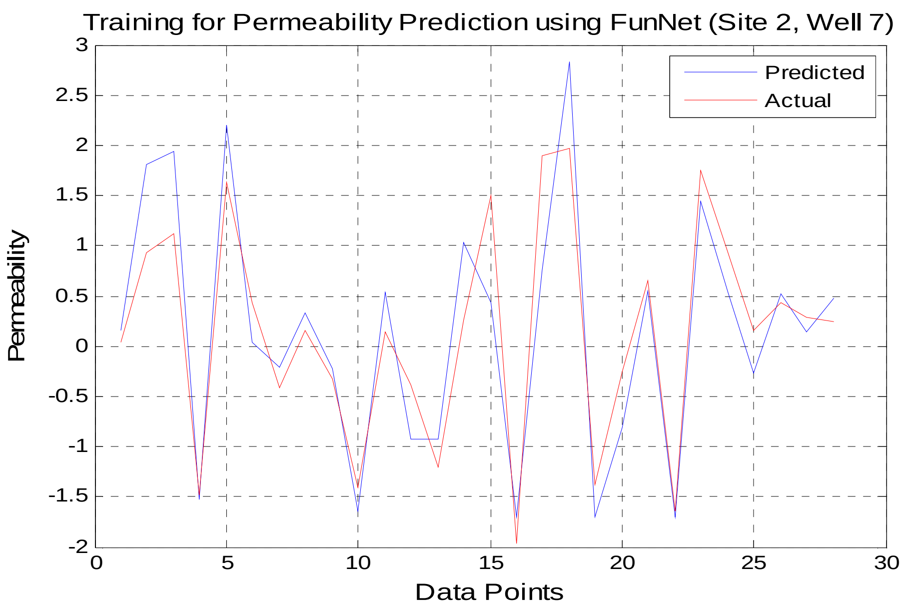

Figure 119: Plot of Actual vs. Predicted Permeability for Site 2, Well 7 (FN Training)

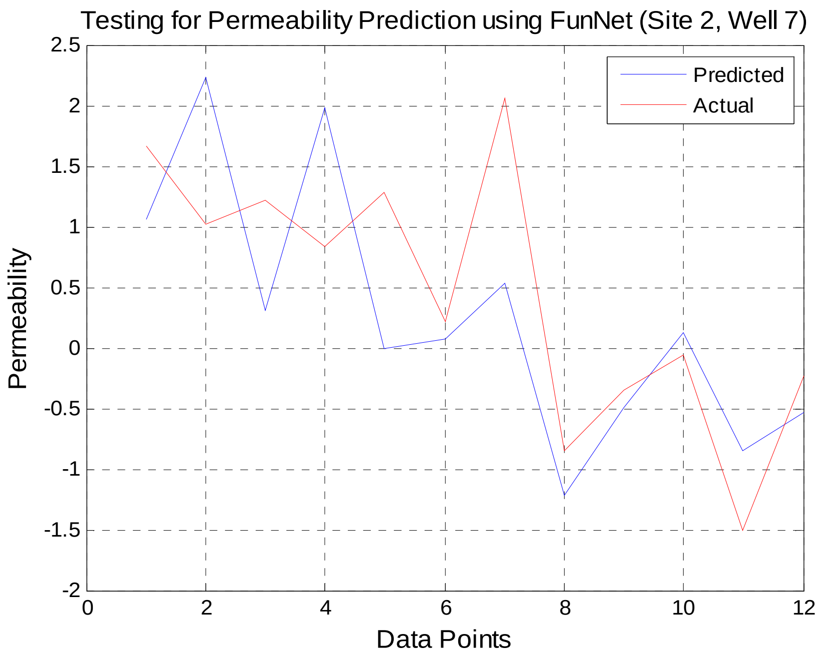

Figure 120: Plot of Actual vs. Predicted Permeability for Site 2, Well 7 (FN Testing)

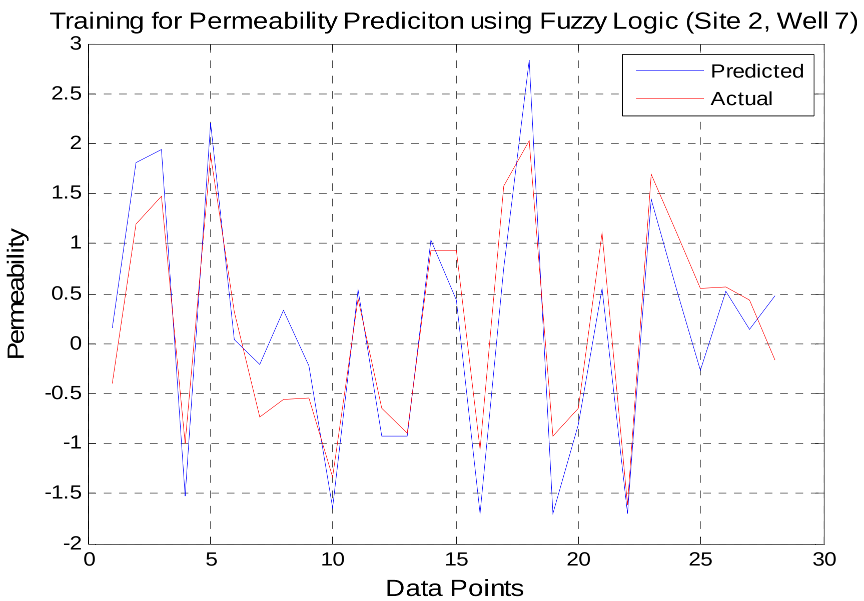

Figure 121: Plot of Actual vs. Predicted Permeability for Site 2, Well 7 (FL Training)

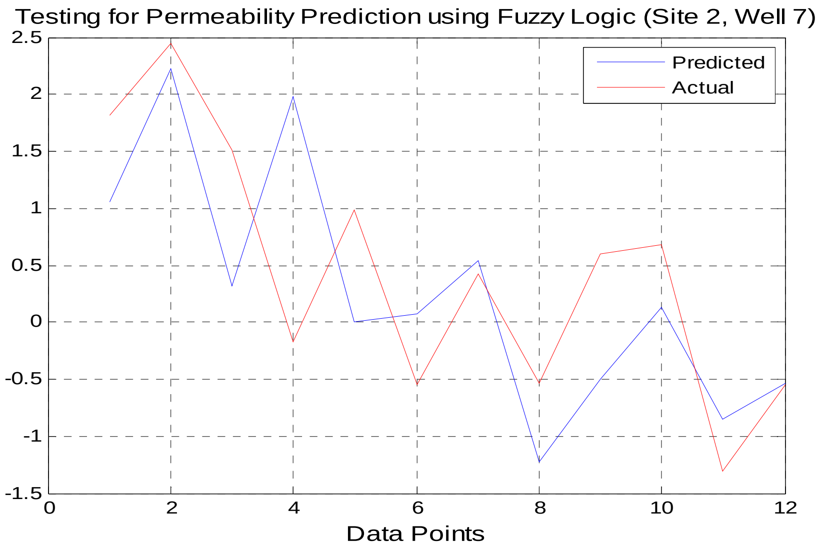

Figure 122: Plot of Actual vs. Predicted Permeability for Site 2, Well 7 (FL Testing)

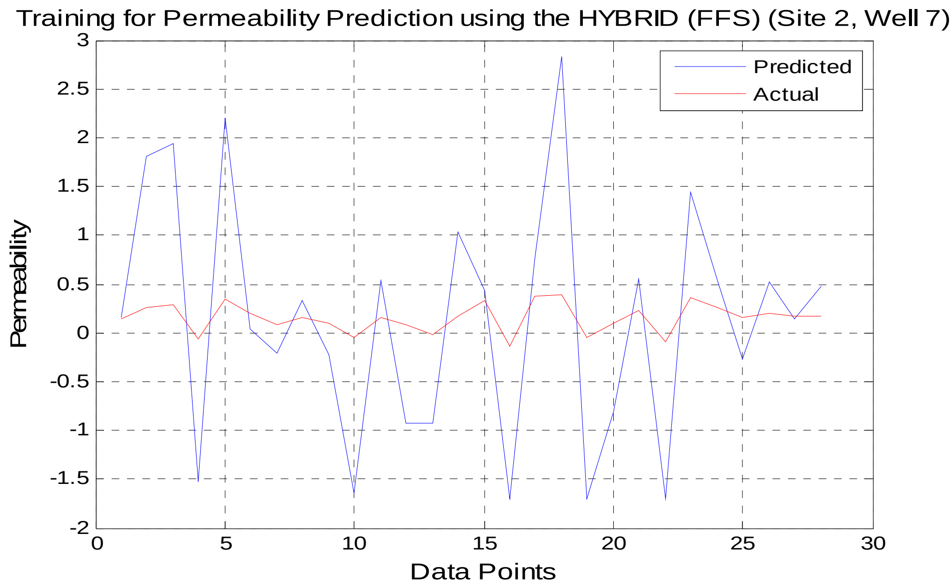

Figure 123: Actual vs. Predicted Permeability for Site 2, Well 7 (FFS Training)

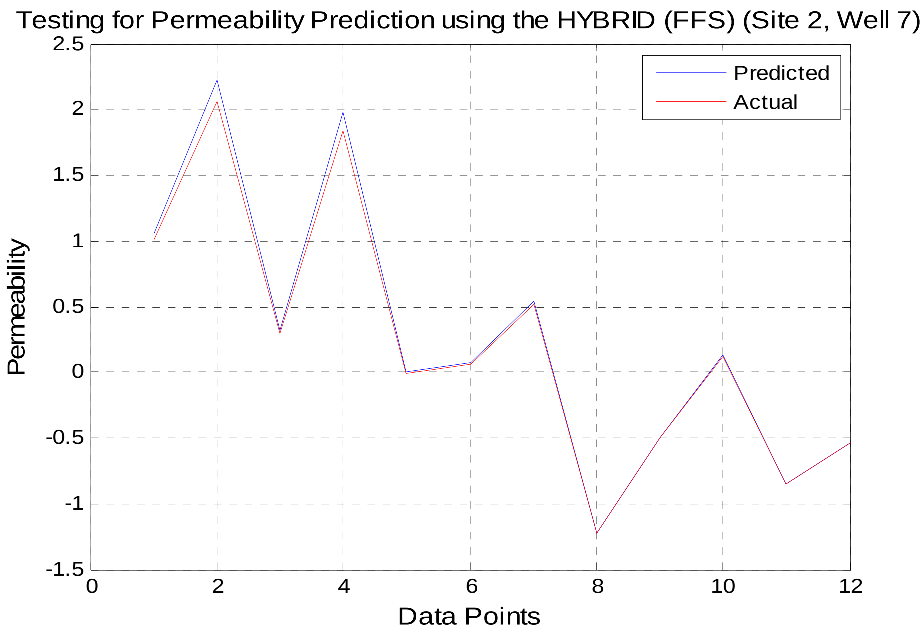

Figure 124: Actual vs. Predicted Permeability for Site 2, Well 7 (FFS Testing)

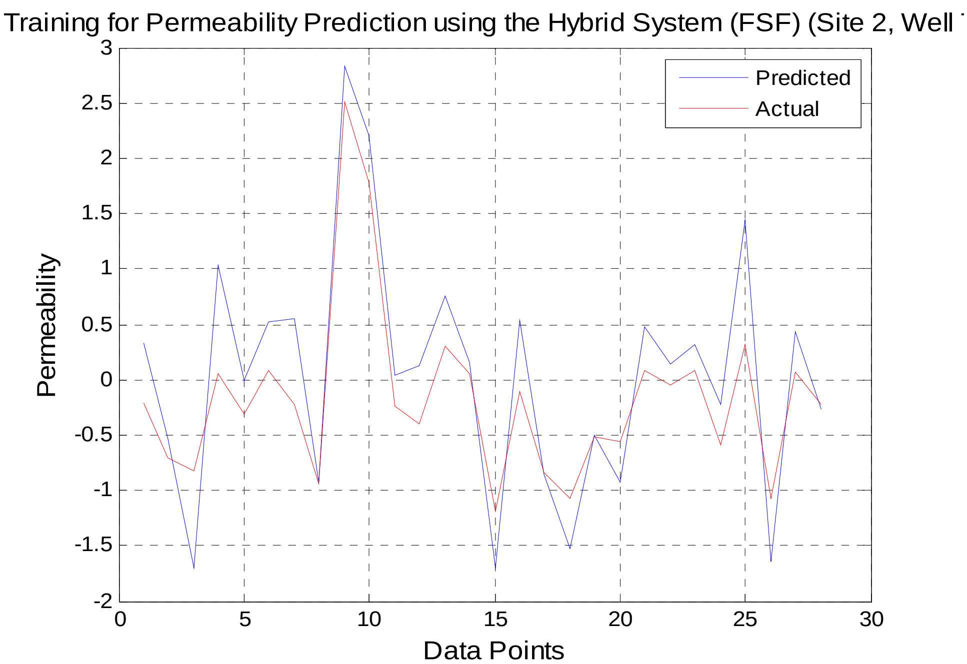

Figure 125: Actual vs. Predicted Permeability for Site 2, Well 7 (FSF Training)

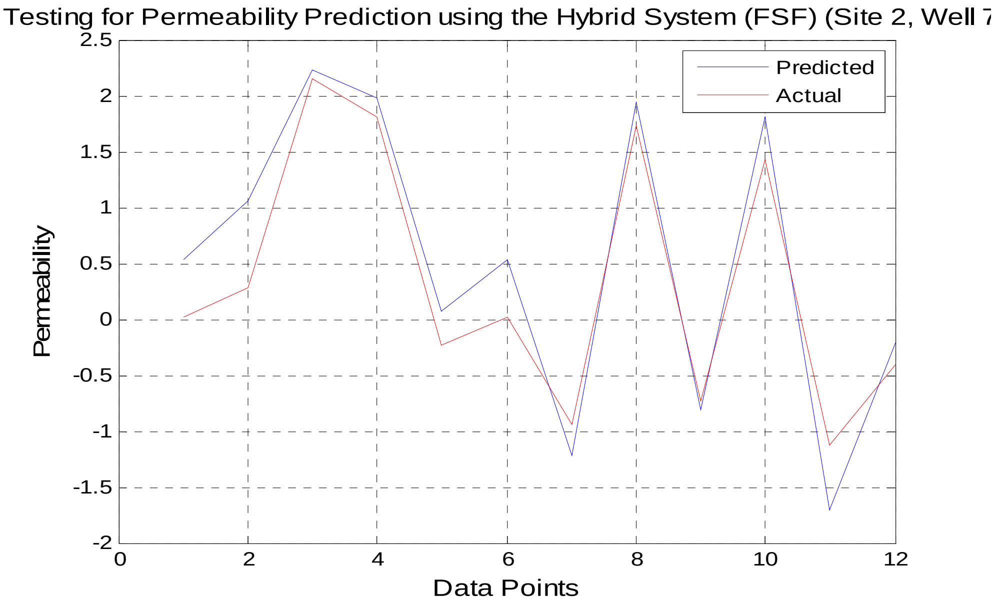

Figure 126: Actual vs. Predicted Permeability for Site 2, Well 7 (FSF Testing)

The comparative results of Correlation Coefficient and Execution times are summarized in Figures 127 to 132.

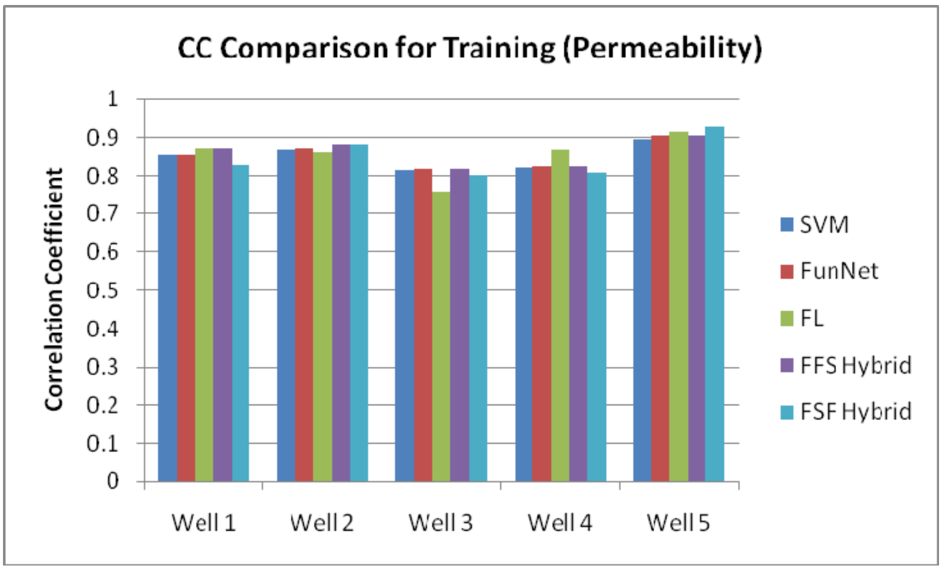

Figure 127: Correlation Coefficients comparisons for Permeability Training

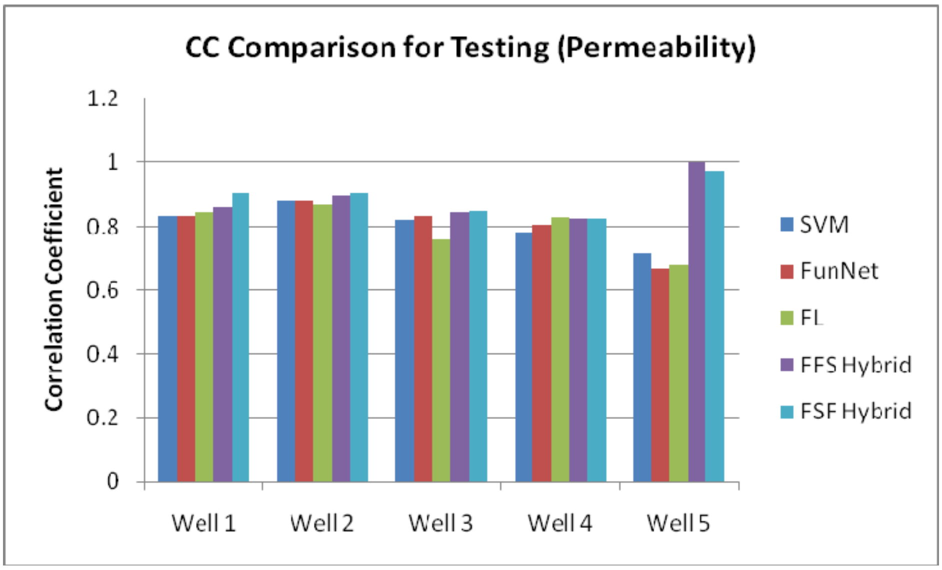

Figure 128: Correlation Coefficients comparisons for Permeability Testing

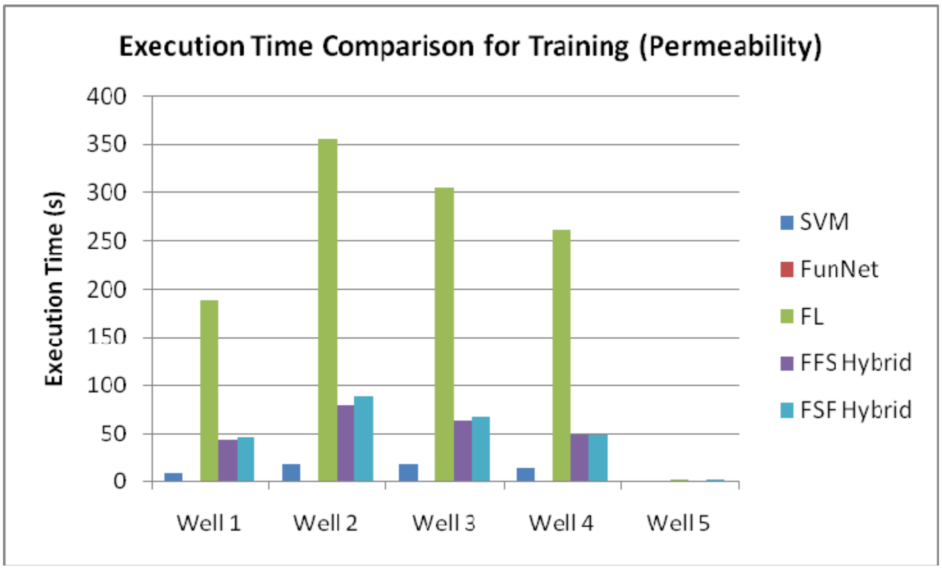

Figure 129: Execution Time comparisons for Permeability Training

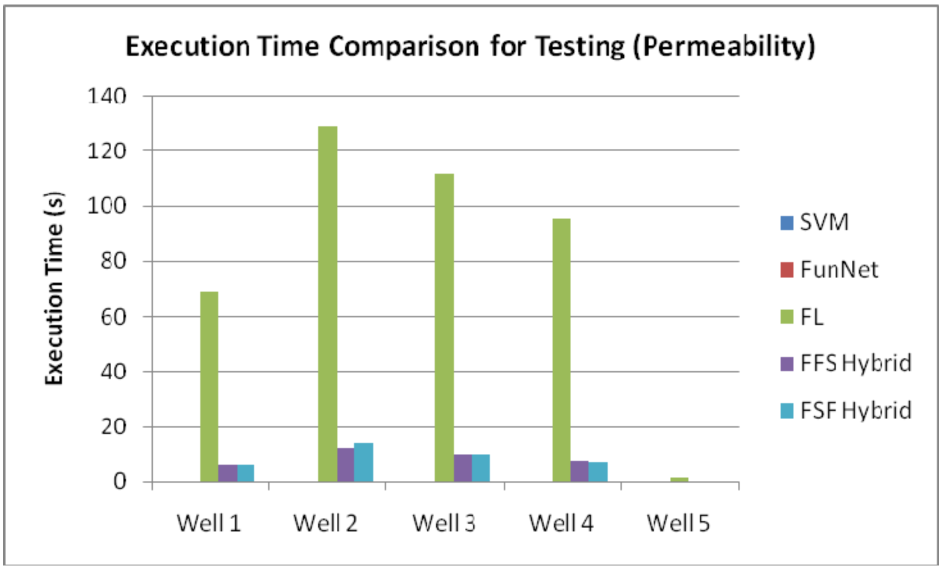

Figure 130: Execution Time comparisons for Permeability Testing

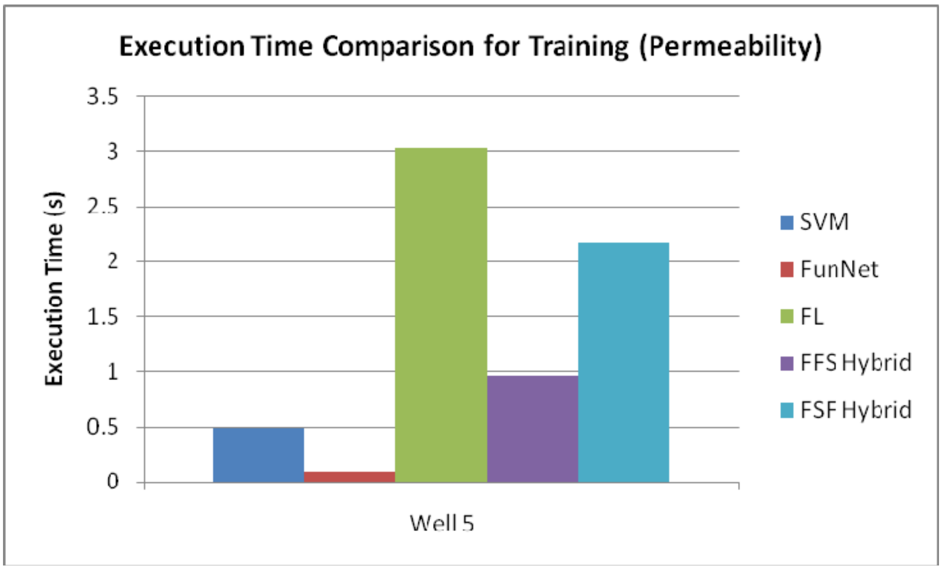

Figure 131: Execution Time comparisons for Permeability Training

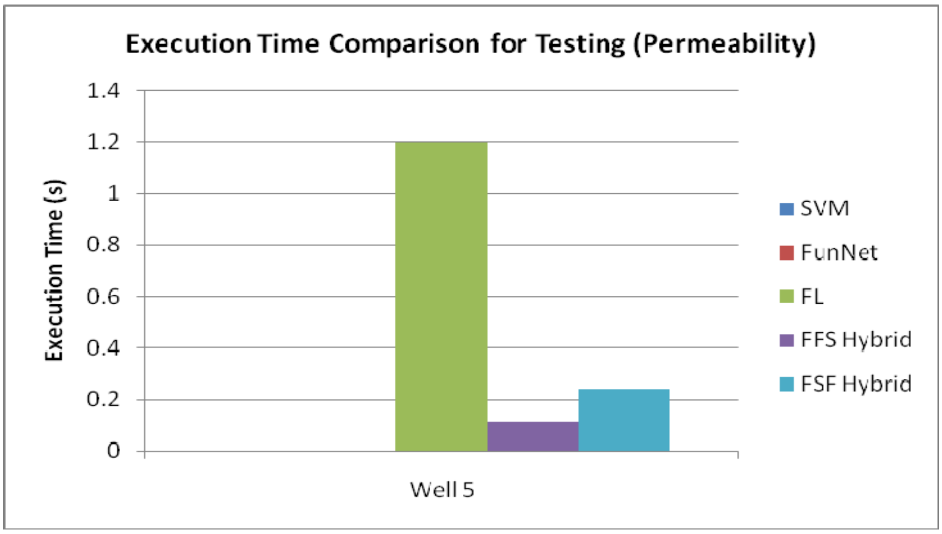

Figure 132: Execution Time comparisons for Permeability Testing

4.4 Prediction of Porosity and Permeability using Type-2 Fuzzy-SVM

In order to appreciate the role performed by the FN block in the FFS and FSF Hybrid models, another set of experiments was performed using only two of the components, namely Type-2 Fuzzy Logic and SVM.

The results of the simulations for the six Porosity and five Permeability wells are summarily shown in table 28 and 29 respectively.

Wells	CC		RMSE		Exec. Time	
Site 1 Well 1	0.811098	0.789864	7.33084	8.64583	297.864583	56.411458
Site 1 Well 2	0.781196	0.700457	7.18849	8.20909	137.381250	26.159375
Site 1 Well 3	0.815213	0.708821	4.61251	5.32429	1.380208	0.125000
Site 2 Well 1	0.857312	0.832355	3.14726	3.19398	128.425000	23.812500
Site 2 Well 2	0.858906	0.848608	3.64437	3.82430	50.130208	9.177083
Site 2 Well 10	0.84644	0.880842	2.78168	2.44552	14.458333	2.661458

Table 28: Results of the simulations for the six Porosity wells

Wells	CC		RMSE		Exec. Time	
Site 2 Well 1	0.814240	0.831428	0.61296	0.61174	358.395833	69.317708
Site 2 Well 2	0.823580	0.817343	0.64555	0.68116	644.093750	125.03125
Site 2 Well 4	0.728086	0.715730	0.90577	0.86452	564.942708	109.015625
Site 2 Well 6	0.796354	0.786183	0.59804	0.64273	489.911458	96.625000
Site 2 Well 7	0.869541	0.706527	0.49529	1.03226	5.427083	0.958333

Table 29: Results of the simulations for the five Permeability wells

Comparisons of the performance of the Type-2-SVM above with the FFS and FSF Hybrids are shown in figures 133 to 140.

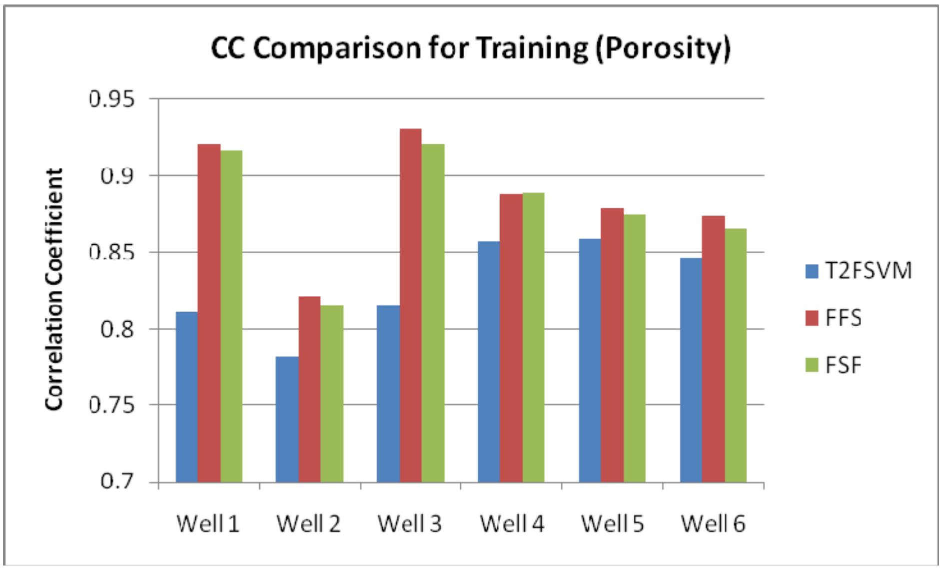

Figure 133: Correlation Coefficient comparisons for Porosity Training

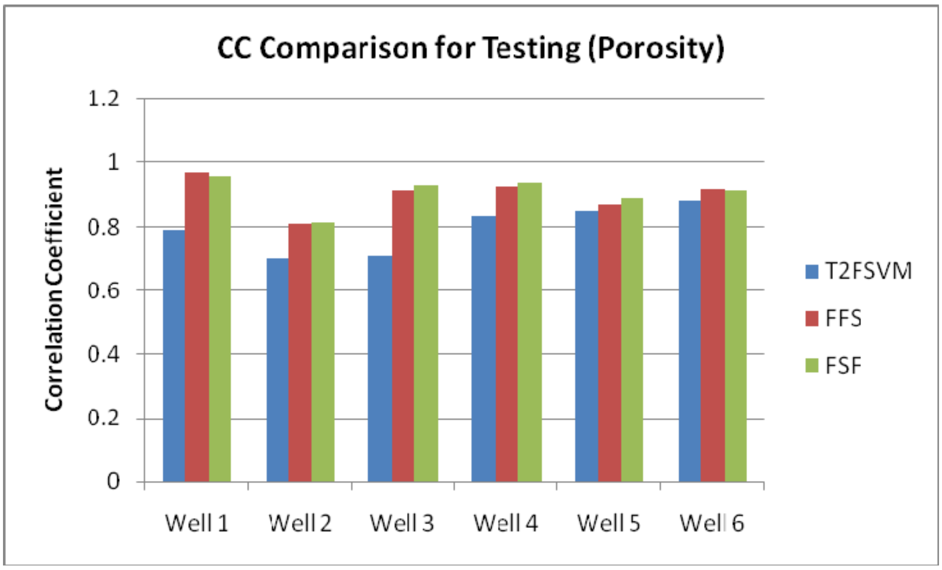

Figure 134: Correlation Coefficient comparisons for Porosity Testing

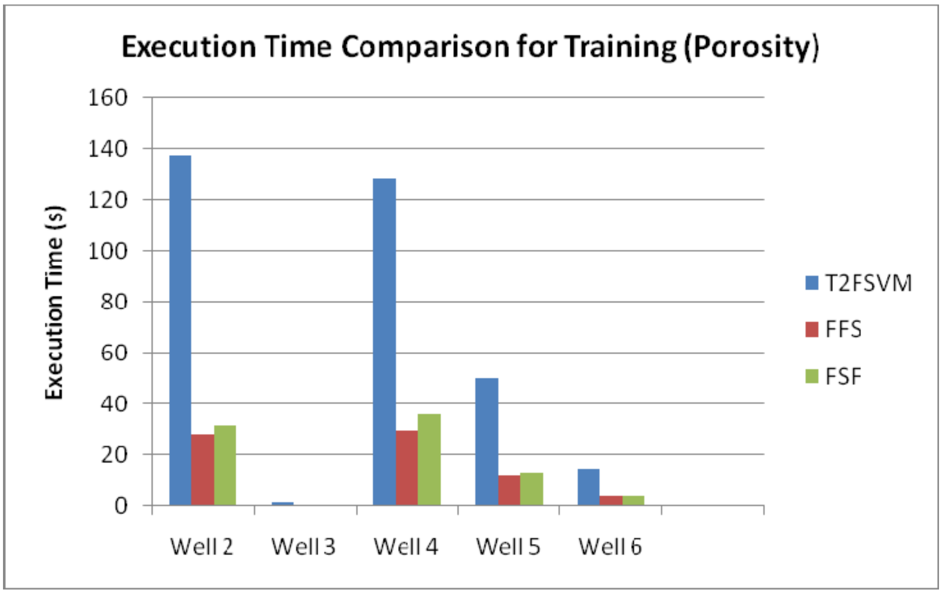

Figure 135: Execution Time comparisons for Porosity Training

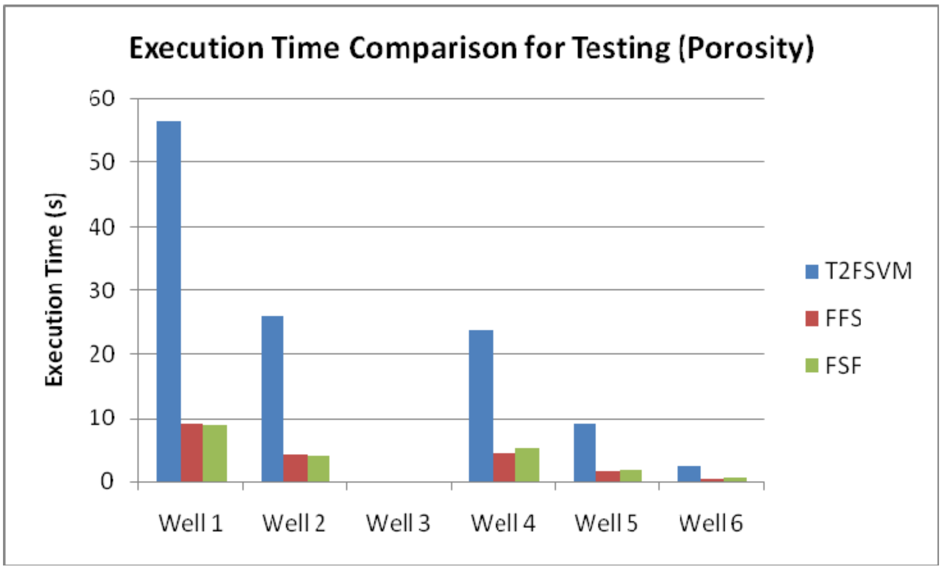

Figure 136: Execution Time comparisons for Porosity Testing

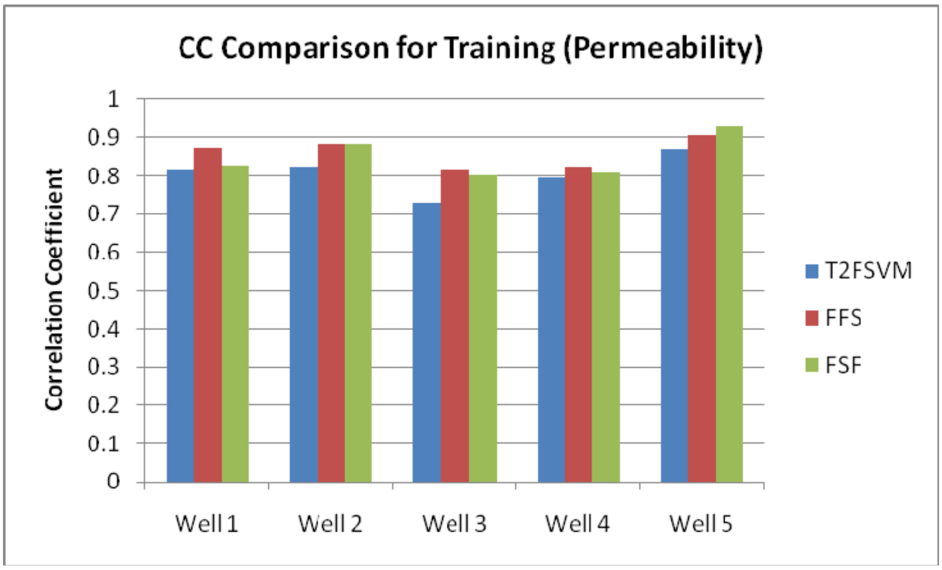

Figure 137: Correlation Coefficient comparisons for Permeability Training

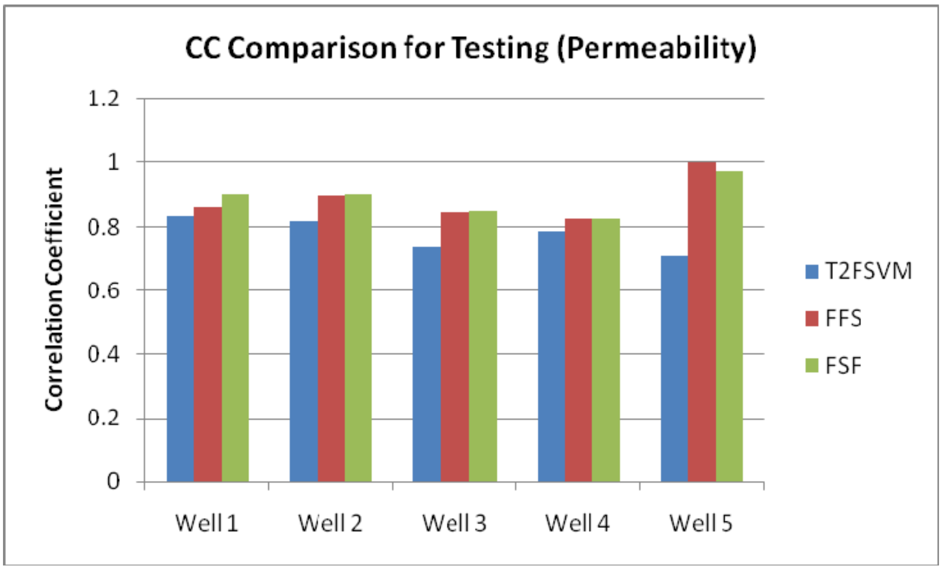

Figure 138: Correlation Coefficient comparisons for Permeability Testing

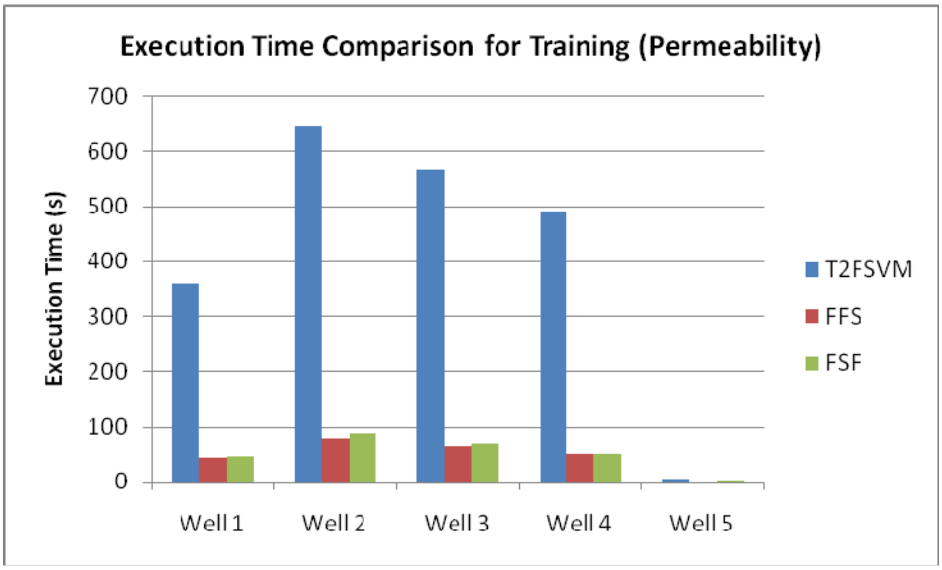

Figure 139: Execution Time comparisons for Permeability Training

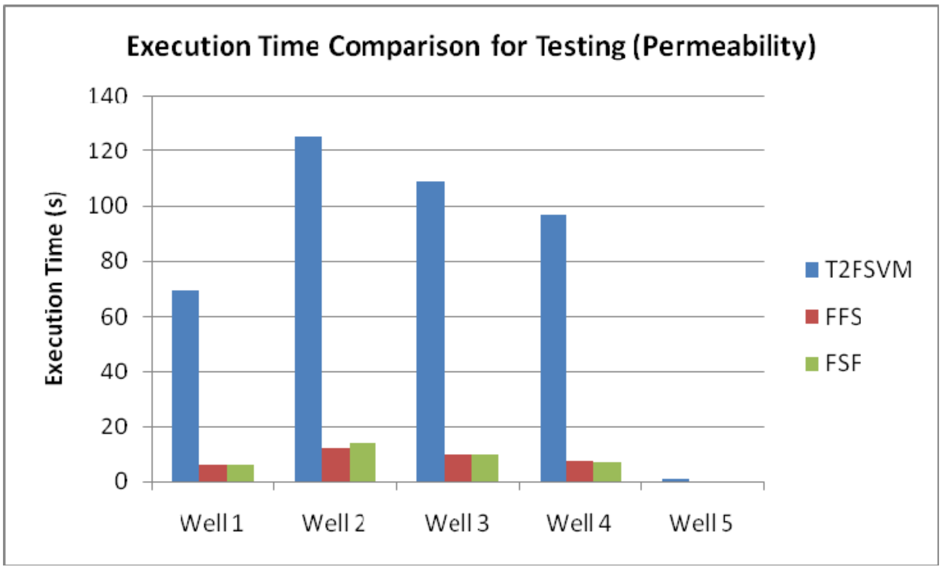

Figure 140: Execution Time comparisons for Permeability Testing

4.5 Discussion of Results

In the prediction of Porosity and Permeability, it is clear from the results that the two hybrid models, in most cases, performed better than, or in some cases, competitively equal to, the three individual techniques used separately, in terms of their correlation coefficient.

A special characteristic was observed in the result of site 1 well 3 for Porosity where SVM demonstrated its ability to withstand a small training data but Fuzzy Logic demonstrated otherwise. Still, the hybrid models performed better than the individual components (including SVM) in testing due to the cooperative spirit that had been built into them.

The two hybrid models were observed to be competitively good, with FSF sometimes performing better than FFS but other times, vice versa. No one of them can be considered superior.

In terms of execution time, the results showed that FN is the fastest in both training and testing, followed by SVM. Fuzzy Logic took the most time to be trained and validated. However, the hybrid models proved to be faster than the Fuzzy Logic component. This is the price one has to pay for a better model in terms of reliability and robustness.

When compared to the Type-2-SVM Hybrid, the FFS and FSF Hybrids also proved to be better in terms of both correlation coefficient and execution time. The better performance in the correlation coefficient can be attributed to the role of Functional Networks in the FFS and FSF hybrids. The Functional Networks block serves as a best-variable selector, which extracts from the input variables only those variables that are most relevant to the prediction system.

The better performance of the FFS and FSF hybrids in terms of execution times is also due to the above reason. In the process of selecting the best variables by the Functional Networks block, the dimensionality of the input variable that goes to the next block (either SVM or Fuzzy Logic) is reduced. This works in favor of the Type-2 Fuzzy that does not work well with an input data of very high dimensionality.

Chapter Five

Conclusion

5.0 Summary

Two novel conceptual design frameworks for the hybridization of Fuzzy Logic, Support Vector Machines and Functional Networks have been implemented and presented. They have been tested using well logs containing six porosity and five permeability datasets obtained from different drilling sites that are geographically differentiated. Each of the individual techniques and their hybrids were developed and tested using the available porosity and permeability data. In the process, the hybrid models were tuned, and the parameters that produce the best results were selected and used for implementation and validation.

The results showed that the two hybrid models performed, in some cases, better than, and, in some other cases, competitively equal to the individual techniques used separately for all the well-logs used in the prediction of Porosity and Permeability. With any available data, the two hybrid models will be able:

- to select the best variables to use directly from the input data using capability of FN;
- to extract inference rules directly from, and handle uncertainties that might be present in, the input data using Fuzzy logic;
- to perform the required regression using the SVM and Fuzzy Logic components.

The capability of Functional Networks as a best-variable selector was also demonstrated by the better performance of the hybrid models over another hybrid model containing only two of the techniques, by excluding Functional Networks. The hybrid models have shown to be very reliable, robust and effective given the reported and observed good performance of the individual components.

5.1 Contribution to Knowledge

This work has achieved the following:

- ✓ New conceptual frameworks for the implementation of two hybrid models, combining Fuzzy Logic, Functional Networks and Support Vector Machines, have been proposed, designed, implemented and validated.
- ✓ Two hybrid models that complement the weaknesses of one AI technique with the strengths of the others, and hence combine the cooperative and competitive characteristics of the individual techniques, have been developed.
- ✓ A software package has been developed for the use of researchers and practitioners of AI for applications in the Oil and Gas industry to predict Porosity and Permeability.
- ✓ This work has confirmed, as already reported in the literature, that hybrids perform better than, or competitively equal to, their individual components used separately.

- ✓ This work is a valuable contribution to knowledge in Petroleum Engineering as well as Computational Intelligence in particular and Computer Science in general.
- ✓ Through this work, academics and practitioners in the application of AI techniques in the oil and gas industries can avail themselves of the inherent advantages of the hybrid models developed as an alternative forecasting tool in their applications.

5.2 Limitation

Despite the good performance of the developed hybrid models, we could not validate the performance of our framework fully because of the lack of fully relevant data.

The design, implementation and validation of the hybrid models were based on well-logs and not on expert knowledge. Furthermore, the Type-2 Fuzzy Logic System, as proposed by Mendel, has some limitations, and our frameworks were built on these limitations. For example, FLS can deal only with Interval Type-2 Gaussian membership functions. It specially imposes the limitation while combining the experts' opinion to deal with linguistic assessment uncertainty.

5.3 Future Work

With the success recorded in this work, our future work will be partly directed towards modifying these hybrid models to solve classification and pattern recognition problems such as Lithofacie and History Matching. With appropriate collaboration, these hybrid models can be extended for use in prediction and classification problems in other areas such as Biometrics.

More experiments can be done on these hybrid models if data is available with uncertain numerical attribute measurements. The frameworks can also then be validated using expert data instead of well-logs.

Type-2 FLS, as developed by Mendel, still has some limitations which have been discussed in the previous section. Some future work can be directed towards this area to make the framework more robust.

References

1. Jong-Se L., "*Reservoir Properties Determination using Fuzzy Logic and Neural Networks from Well Data in Offshore Korea*", Journal of Petroleum Science and Engineering 49, 182– 192, 2005.
2. David H. and Stanley L., "*Applied Logistic Regression*", John Wiley and Sons, 2nd Edition, pp. 1-11, July 2000.
3. Akram S., Syed R. and Kumar N., "*An Enhancement of k-Nearest Neighbor Classification Using Genetic Algorithm*", Midwest Instruction and Computing Symposium, pp. 1-13, 2005.
4. Włodzisław D., Rafał A., and Norbert J., "*Initialization and Optimization of Multilayered Perceptrons"*, Third Conference on Neural Networks and their Applications, Kule, Poland, pp. 1-6, 1997.
5. Li G., "*Radial Basis Function Neural Network for Speaker Verification"*, A Master thesis submitted to the Nanyang Technological University, Pp. 1-104, 2004.
6. Eitel J.M. and Peter J. D., "*A Bayesian Belief Network for IT Implementation Decision Support*", Decision Support Systems and IFIP International Conference on Decision Support Systems, 2006.
7. El-Sebakhy E., "*Software Reliability Identification using Functional Networks: A Comparative Study"*, Expert Systems with Applications, ScienceDirect, 2008.
8. El-Sebakhy E., Raharja I. and Khaeruzzaman Y., "*Machine Learning and Data Mining Tools for the Pattern Recognition: Theory and Applications*", submitted to Elsevier Science, pp. 1-117, 2006.
9. Jun H., "*Computational Intelligence*", Research Interests, http://www.cs.bham.ac.uk/~jxh/hejunrs.html, 2008.
10. Giovanni A. and Vincenzo L., "*Using FML and Fuzzy Technology in Adaptive Ambient Intelligence Environments*", International Journal of Computational

Intelligence Research, Research India Publications http://www.ijcir.info, ISSN 0973-1873 Vol.1, No.2 (2005), pp. 171–182.

11. Andreas L.S. and Pericles A.M., *"Agent Intelligence through Data Mining*", Multi-agent Systems, Artificial Societies, and Simulated Organizations Series, Volume 14, International Book Series, pp. 65, 2005.
12. Evangelos T. and Giovanni F., "*Data Mining and Knowledge Discovery Approaches Based on Rule Induction Techniques*", Springer Science-i-Business Media, P. 526, 2006.
13. Toshinori M., "*Fundamentals of the New Artificial Intelligence Neural, Evolutionary, Fuzzy and More*", 2nd Edition, Springer Science+Business Media, 2008.
14. Gloria P., Nikhil I. and Lakhmi C., "*Intelligent Decision Making: An AI-Based Approach*", Studies in Computational Intelligence, Volume 97, Springer-Verlag Berlin Heidelberg, P. 88, 102, 355, 2008.
15. Nong Y., "*The Handbook of Data Mining*", Lawrence Erlbaum Associates, P. 561, 617, 2003.
16. Lipo W. and Xiuju F., "*Data Mining with Computational Intelligence*", Springer-Verlag Berlin Heidelberg, pp. 195-208, 2005.
17. Sandhya P., Ajith A., Crina G. and Johnson T., "*Modeling Intrusion Detection System using Hybrid Intelligent Systems*", Journal of Network and Computer Applications, 30, pp. 114–132, 2007.
18. Zhan-Li S., Kin-Fan A., and Tsan-Ming C., "*A Neuro-Fuzzy Inference System through Integration of Fuzzy Logic and Extreme Learning Machines*", IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics, Vol. 37, No. 5, October 2007, Pp. 1321-1331.
19. Mohaghegh, S., Arefi, R. and Ameri, S., "*Design and Development of an Artificial Neural Network for Prediction of Formation Permeability*", Society of Petroleum Engineers (SPE) paper 28237 presented at the 1994 SPE Petroleum Computer Conference, July 31-August 3, Dallas.

20. Ali J.K., “*Neural Networks: A New Tool for the Petroleum Industry*”, European Petroleum Computer Conference, Aberdeen, U.K., pp. 217-231, March 1994.
21. Habiballah W.A., Startzman R.A. and Barrufet M.A., “*Use of Neural Networks for Prediction of Vapor/Liquid Equilibrium K-Values for Light Hydrocarbon Mixtures*”, Society of Petroleum Engineers Annual Technical Conference and Exhibition in New Orleans, LA, Sept 25-28, 1996.
22. Briones M.F., Rojas G.A., Moreno J.A. and Martinez E.R., "*Application of Neural Networks in the Prediction of Reservoir Hydrocarbon Mixture Composition from Production Data*", Society of Petroleum Engineers Annual Technical Conference and Exhibition in New Orleans, LA, Sept 25-28, 1996.
23. Martin K.D., Geoffrey C.B., Alan P.B. and Shane C.S., "*Extracting Lithofacies from Digital Well Logs Using Artificial Intelligence, Panoma (Council Grove) Field, Hugoton Embayment, Southwest Kansas*", Kansas Geological Survey Open-file Report, Volume 68, 2003.
24. Hsien-Cheng C., David K. and Hui-Chuan C., “*Identification of Lithofacies using Kohonen Self-organizing Maps*”, Computers & Geosciences 28, 2002, Pp. 223–229.
25. Hsien-Cheng C., David K., Hui-Chuan C. and Rocky D., "*Lithofacies Identification using Multiple Adaptive Resonance Theory Neural Networks and Group Decision Expert System*", Computers & Geosciences 26, 2000, Pp. 591-601.
26. Lianshuang Q. and Timothy C., "*Neural Network Prediction of Carbonate Lithofacies from Well Logs, Big Bow and Sand Arroyo Creek fields, Southwest Kansas*", Computers & Geosciences 32, 2006, Pp. 947–964.
27. Gharbi R.B. and El-Sharkawy A.M., “*Neural Network Model for Estimating the PVT Properties of Middle East Crude Oils*”, 1997 Society of Petroleum Engineers Middle East Oil Show, Bahrain, March, 1997.
28. Gharbi R.B. and El-Sharkawy A.M., “*Universal Neural Network Based Model for Estimating the PVT Properties of Crude Oil Systems*”, 1997 Society of

Petroleum Engineers Asia Pacific Oil and Gas Conference, Malaysia, April, 1997.

29. Osman E.A. and Al-Marhoun M.A., "*Artificial Neural Networks Models for Predicting PVT Properties of Oil Field Brines*", 14th Society of Petroleum Engineers Middle East Oil & Gas Show and Conference held in Bahrain International Exhibition Centre, Bahrain, 12–15 March 2005.
30. Alcocer Y. and Rodrigues P., "*Neural Networks Models for Estimation of Fluid Properties*", Society of Petroleum Engineers Latin American and Caribbean Petroleum Engineering Conference held in Buenos Aires, Argentina, 25–28 March 2001.
31. Hussam G., El-Shokir E., Khaled F. and Mohamed S., "*Prediction of the PVT Data using Neural Network Computing Theory*", 27th Annual Society of Petroleum Engineers International Technical Conference and Exhibition in Abuja, Nigeria, August 4-6, 2003.
32. Elsharkawy A., "*Modeling the Properties of Crude Oil and Gas Systems Using RBF Network*", 1998 Society of Petroleum Engineers Asia Pacific Oil & Gas Conference and Exhibition held in Perth, Australia, 12-14 October, 1998.
33. Abdelkader E., Djebbar T. and Amine M., "*Application of Artificial Intelligence to Characterize Naturally Fractured Zones in Hassi Messaoud Oil Field, Algeria*", Journal of Petroleum Science and Engineering, Vol. 49, 2005, Pp. 122– 141.
34. El-sharkawy A. and Salah F., "*EOS Simulation and GRNN Modeling of the Constant Volume Depletion Behavior of Gas Condensate Reservoirs*", Energy & Fuels, Volume 12, 1998, Pp. 353-364.
35. Jamialahmadi M. and Javadpour F.G., "*Relationship of permeability, porosity and depth using an artificial neural network*", Journal of Petroleum Science and Engineering 26, 2000, Pp. 235–239.
36. Schlumberger Excellence in Educational Development, Science Lab Project, http://www.seed.slb.com/en/scictr/lab/porosity/index.htm, 2007

37. Schlumberger Excellence in Educational Development, Science Lab Project, http://www.seed.slb.com/en/scictr/lab/permeability/index.htm, 2007.
38. Bill S., "*Introduction to Groundwater Flow*", Lecture Notes, Department of Civil Engineering, University of Glasgow, 2007.
39. King Saud University, KSU Electronic document Archive, docs.ksu.edu.sa/DOC/Articles49/Article490822.doc, 2007.
40. Mohsen S., Morteza A. and Ali Y.V., "*Design of neural networks using genetic algorithm for the permeability estimation of the reservoir*", Journal of Petroleum Science and Engineering 59, 97–105, 2007.
41. Maqsood A. and Adwait C., "*Using Artificial Intelligence to Predict Permeability from Petrographic Data*", Computers & Geosciences 26, 915 - 925, 2000.
42. Yuantu H., Tom G. and Patrick W., "*An Integrated Neural-Fuzzy-Genetic-Algorithm using Hyper-Surface Membership Functions to Predict Permeability in Petroleum Reservoirs*", Engineering Applications of Artificial Intelligence 14, 15-21, 2001.
43. Jong-Se L., "*Reservoir Properties Determination using Fuzzy Logic and Neural Networks from Well Data in Offshore Korea*", Journal of Petroleum Science and Engineering 49, 182– 192, 2005.
44. Karnik N. and Mendel J., "*Type-2 Fuzzy Logic Systems", IEEE Transactions on Fuzzy Systems*", Vol. 7, No. 6, December 1999.
45. Mendel, J. M., "*Type-2 Fuzzy Sets: Some Questions and Answers*," IEEE Connections, Newsletter of the IEEE Neural Networks Society, vol. 1, Aug. 2003, pp. 10-13.
46. Mendel, J. M. and John, R. I. (2002). "*Type-2 Fuzzy Sets Made Simple*", IEEE Transactions on Fuzzy Systems, vol. 10, pp. 117-127.
47. Zarandi F.H., Pourakbar M. and Turksen I.B., "*A Fuzzy Agent-Based Model for Reduction of Bullwhip Effect in Supply Chain Systems*", Expert Systems with Applications (2007), doi:10.1016/j.eswa.2007.01.031

48. Zarandi F.H. and Mohammad E., "*A Systematic Fuzzy System Modeling for Scheduling of Textile Manufacturing System*", International Journal of Management Science and Engineering Management, Vol. 2, 2007, No. 4, pp. 297-308.
49. Castillo O., Cazarez N. and Melin P., "*Design of Stable Type-2 Fuzzy Logic Controllers based on a Fuzzy Lyapunov Approach*", 2006 IEEE International Conference on Fuzzy Systems, Vancouver, Canada, July 16-21, 2006, Pp. 2331-2336.
50. Zarandi, M.H., Rezaee, B., Turksen, I.B. and Neshat, E., "*A Type-2 Fuzzy Rule-Based Expert System Model for Stock Price Analysis*", Expert Systems with Applications (2007), doi: 10.1016/j.eswa.2007.09.034.
51. Castillo O., Aguilar L., Cazarez N. and Cardenas S., "*Systematic Design of a Stable Type-2 Fuzzy Logic Controller*", Applied Soft Computing Journal (2007), doi:10.1016/j.asoc.2007.02.021.
52. Dongrui W. and Woei W.T., "*Genetic Learning and Performance Evaluation of Interval Type-2 Fuzzy Logic Controllers*", Engineering Applications of Artificial Intelligence 19, pp. 829–841, Elsevier, 2006.
53. Dongrui W. and Mendel J.M., "*A Vector Similarity Measure for Linguistic Approximation: Interval Type-2 and Type-1 Fuzzy Sets*", Information Sciences 178, pp. 381–402, 2008.
54. John R.I. and Czarnecki C., "*An Adaptive Type-2 Fuzzy System for Learning Linguistic Membership Grades*", IEEE International Fuzzy Systems Conference Proceedings, August 22-25, 1999. Seoul, Korea, Pp. 1552-1556.
55. Li Y., Sun X., Hua J. and Gong C., "*Modelling Redundant Structure in Ecosystem by Type-2 Fuzzy Logic System*", Ecological Modeling, Article in Press, Elsevier, 2007.
56. Maria L.A., Hernandez M. and Gerardo M., "*Modeling and Prediction of the MXNUSD Exchange Rate Using Interval Singleton Type-2 Fuzzy Logic Systems*", 2006 IEEE International Conference on Fuzzy Systems Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada, July 16-21, 2006.

57. Zarandi F.H., Turksen I.B. and Torabi K.O., "*Type-2 Fuzzy Modeling for Desulphurization of Steel Process*", Expert Systems with Applications 32, 2007, 157–171.
58. Murari A., Vagliasindi G., Zedda M.K. and Sammon C., "*Fuzzy Logic and Support Vector Machine Approaches to Regime Identification in JET*", IEEE Transactions on Plasma Science, 2005.
59. Fang J.H. and Chen H.C., "*Fuzzy Modeling and the Prediction of Porosity and Permeability from the Compositional and Textural Attributes of Sandstone*", Journal of Petroleum Geology, vol. 20(2), April 1997, pp. 185-204.
60. El-Sebakhy E., Sheltami T., Al-Bokhitan S., Shaaban Y., Raharja I. and Khaeruzzaman Y., "*Support Vector Machines Framework for Predicting the PVT Properties of Crude-Oil Systems*", 15th Society of Petroleum Engineers Middle East Oil & Gas Show and Conference, Bahrain, March 2007.
61. El-Sebakhy E., "*Artificial Neural Networks, Probabilistic Networks, Support Vector Machines, Adaptive-Neuro Fuzzy Systems, and Functional Networks*", submitted to Elsevier Science, 2006.
62. Littman W., "*Introduction to Support Vector Machines*", Lecture notes on CS 536: Machine Learning, Department of Computer Science, Rutgers, The State University of New Jersey, USA.
63. Terrence S.F., Nello C., Nigel D., David W.B., Michel S. and David H., "*Support Vector Machine Classification and Validation of Cancer Tissue Samples using Microarray Expression Data*", Bioinformatics, Vol. 16, 10, 2000, Pp. 906-914.
64. Goda H.M., Maier, H.R. and Behrenbruch, P., "*Use of Artificial Intelligence Techniques for Predicting Irreducible Water Saturation - Australian Hydrocarbons Basins*", Society of Petroleum Engineers Asia Pacific Oil & Gas Conference and Exhibition, Jakarta, Indonesia, 2007.
65. Zhao C.Y., Zhang H.X., Liu M.C., Hua Z.D. and Fan B.T., "*Application of Support Vector Machine (SVM) for Prediction Toxic Activity of Different Data Sets*", Toxicology 217, 2006, Pp. 105–119.

66. Vannerem P., Muller K.R., Scholkopf B., Smola A. and Soldner-Rembold S., "*Classifying LEP Data with Support Vector Algorithms*", Proceedings of AIHENP'99, hep-ex/9905027, Crete, April 1999.
67. Jian H. and Wenfen H., "*Novel Approach to Predict Potentiality of Enhanced Oil Recovery*", Society of Petroleum Engineers Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands, 2006.
68. Van G.T., Baesens, B., Suykens, J., Espinoza, M., Baestaens, D.E., Vanthienen, J. and De-Moor, B., "*Bankruptcy Prediction with Least Squares Support Vector Machine Classifiers*", Proceedings of IEEE International Conference on Computational Intelligence for Financial Engineering, pp. 1-8, 20-23 March 2003.
69. Stephan K.C., Tobias D. and Detlef S., "*Classification of Ebay Bidding Characteristics*", International Association of Development of the Information Society International Journal on WWW/Internet, Vol. 4, No. 1, pp. 111-125, 2005.
70. Christopher J.C., "*A Tutorial on Support Vector Machines for Pattern Recognition*", Data Mining and Knowledge Discovery 2, 121-167, 1998.
71. Gang W. and Edward Y.C., "*Class-Boundary Alignment for Imbalanced Dataset Learning*", Workshop on Learning from Imbalanced Datasets II, International Conference on Machine Learning (ICML), Washington DC, 2003.
72. Emre C., Ahmet A. and Türkoglu I., "*A Decision Support System Based on Support Vector Machines for Diagnosis of the Heart Valve Diseases*", Computers in Biology and Medicine 37, 2007, Pp. 21 – 27.
73. Kristof C. and Dirk V.P., "*Churn prediction in Subscription Services: An Application of Support Vector Machines while Comparing Two Parameter-Selection Techniques*", Expert Systems with Applications 34, 2008, Pp. 313–327.
74. Kemal P. and Salih G., "*Breast Cancer Diagnosis using Least Square Support Vector Machine*", Digital Signal Processing 17, 2007, Pp. 694–701.

75. Taboada J., Matías J.M., Ordóñez C. and García P.J., “*Creating a Quality Map of a Slate Deposit using Support Vector Machines*”, Journal of Computational and Applied Mathematics 204, pp 84 – 94, Elsevier, 2007.
76. Jin-Hyuk H., Jun-Ki M., Ung-Keun C. and Sung-Bae C., "*Fingerprint Classification using One-vs-All Support Vector Machines Dynamically Ordered with Naïve Bayes Classifiers*", Pattern Recognition, Vol. 41, 2008, Pp. 662 – 671.
77. Kemal P., Salih G. and Ahmet A., "*A Cascade Learning System for Classification of Diabetes Disease: Generalized Discriminant Analysis and Least Square Support Vector Machine*", Expert Systems with Applications 34, 2008, Pp. 482–487.
78. Elish, K.O. and Elish, M.O., “*Predicting Defect-Prone Software Modules Using Support Vector Machines*”, The Journal of Systems and Software (2007), doi: 10.1016/j.jss.2007.07.040
79. Cheng-Lung H., Hung-Chang L. and Mu-Chen C., "*Prediction Model Building and Feature Selection with Support Vector Machines in Breast Cancer Diagnosis*", Expert Systems with Applications 34, 2008, Pp. 578–587.
80. Li, X., Luan, F., Si, H., Hu, Z. and Liu, M., "*Prediction of Retention Times for a Large Set of Pesticides or Toxicants Based on Support Vector Machine and the Heuristic Method*", Toxicology Letters (2007), doi:10.1016/j.toxlet.2007.10.005
81. Jie W., Hongying D., Huanxiang L., Xiaojun Y., Zhide H. and Botao F., "*Prediction of Surface Tension for Common Compounds Based on Novel Methods using Heuristic Method and Support Vector Machine*", Talanta 73, 2007, 147–156.
82. Ciwei G., Ettore B., Roberto N. and Haozhong C., "*Price Forecast in the Competitive Electricity Market by Support Vector Machine*", Physica A 382, 2007, 98–113.

83. Anthony T.C. Goh and S.H. Goh, "*Support Vector Machines: Their Use in Geotechnical Engineering as Illustrated using Seismic Liquefaction Data*", Computers and Geotechnics 34, 2007, 410–421.

84. Castillo E., "*Functional Networks*", Neural Processing Letters 7: 151–159, 1998.

85. El-Sebakhy E., Hadi A.S. and Kanaan F.A., "*Iterative Least Squares Functional Networks Classifier*", IEEE Transactions on Neural Networks, Vol. 18, No. 2, pp. 1-7, March 2007.

86. Castillo E., Hadi A. and Lacruz B., "*Optimal Transformations in Multiple Linear Regression using Functional Networks*", International Work-Conference on Artificial and Natural Neural Networks, 2001, Lecture Notes in Computer Science 2084, pp. 316-324, 2001.

87. Castillo, E., Gutiérrez, J.M., Hadi, A.S. and Lacruz, B., "*Some Applications of Functional Networks in Statistics and Engineering*", Technometrics, 43, Pp. 10–24, 2001.

88. Chen X., Li Y., Harrison R. and Zhang Y.Q., "*Type-2 Fuzzy Logic Based Classifier Fusion for Support Vector Machines*", Applied Soft Computing Journal, 2007, doi:10.1016/j.asoc.2007.02.019.

89. Melin, P. and Castillo, O.; "*Intelligent Control of Non-Linear Plants Using Type-2 Fuzzy Logic and Neural Networks*", Proceedings of the International Joint Conference on Neural Networks, Volume 2, 20-24 July 2003 Page(s):1558 – 1562. Digital Object Identifier 10.1109/IJCNN.2003.1223930.

90. Chi-Hsu W., Chun-Sheng C. and Tsu-Tian L., "*Dynamical Optimal Training for Interval Type-2 Fuzzy Neural Network (T2FNN)*", IEEE Transactions on Systems, Man, and Cybernetics, Part B, 2004: 1462~1477.

91. Ferraz I.N. and Garcia C.B., "*Lithofacies Recognition Hybrid Bench*", Proceedings of the Fifth International Conference on Hybrid Intelligent Systems (HIS'05), IEEE, 0-7695-2457-5/05 $20.00, 2005.

92. Salim C., "*A Fuzzy ART versus Hybrid NN-HMM Methods for Lithology Identification in the Triasic Province*", IEEE Transactions, 0-7803-9521-2/06, 2006.
93. Mendoza, O., Licea, G. and Melin, P., "*Modular Neural Networks and Type-2 Fuzzy Logic for Face Recognition*", Annual Meeting of the North American Fuzzy Information Processing Society, 2007 (NAFIPS '07), 24-27 June 2007 Page(s):622 - 627.
94. Ho T.L. and Ehara S., "*Oil Reservoir Properties Estimation by Fuzzy-Neural Networks*", Memoirs of the Faculty of Engineering, Kyushu University, Vol.67, No.3, September 2007.
95. Chikhi S. and Batouche M., "*Probabilistic Neural Method Combined with Radial-Bias Functions Applied to Reservoir Characterization in the Algerian Triassic Province*", Journal of Geophysics and Engineering, 1 (2004), Pp. 134–142.
96. Deyi X., Dave W., Tina Y. and San R., "*Permeability Estimation Using a Hybrid Genetic Programming and Fuzzy/Neural Inference Approach*", 2005 Society of Petroleum Engineers Annual Technical Conference and Exhibition held in Dallas, Texas, U.S.A., 9 - 12 October 2005.
97. Taylor J.G., "*Neural Computation: The Background*", Handbook of Neural Computation release 97/1, Institute of Physics Publishing Ltd and Oxford University Press, 1997.
98. http://www.neurocomputing.org/
99. Jin B., Tang Y.C. and Yan-Qing Z., "*Support Vector Machines with Genetic Fuzzy Feature Transformation for Biomedical Data Classification*", Information Sciences 177 (2007), Pp. 476–489.
100. Yixin C. and James Z.W., "*Support Vector Learning for Fuzzy Rule-Based Classification Systems*", IEEE Transactions on Fuzzy Systems, Vol. 11, No. 6, December 2003.

101. Sandhya P., Ajith A., Crina G. and Johnson T., "*Modeling Intrusion Detection System using Hybrid Intelligent Systems*", Journal of Network and Computer Applications 30 (2007), Pp. 114–132.

102. Evaggelos S., Giorgos S., Yannis A. and Stefanos K., "*Fuzzy Support Vector Machines For Image Classification Fusing Mpeg-7 Visual Descriptors*", Image, Video and Multimedia Systems Laboratory, School of Electrical and Computer Engineering, National Technical University of Athens, Greece, 2006.

103. Abe S., "*Fuzzy LP-SVMs for Multiclass Problems*", Proceedings of European Symposium on Artificial Neural Networks (ESANN'2004) Bruges, Belgium, 28-30 April 2004, d-side Publisher, ISBN 2-930307-04-8, pp. 429-434.

104. Lean Y., Kin K.L. and Shouyang W., "*Credit Risk Assessment with Least Squares Fuzzy Support Vector Machines*", Sixth IEEE International Conference on Data Mining - Workshops (ICDMW'06), 0-7695-2702-7/06, 2006.

105. Zhan-Li S., Kin-Fan A. and Tsan-Ming C., "*A Neuro-Fuzzy Inference System Through Integration of Fuzzy Logic and Extreme Learning Machines*", IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, Vol. 37, No. 5, Pp. 1321 - 1331, October 2007.

106. Mohaghegh, S., Balan, B., Ameri, S., and McVey, D.S., "*A Hybrid, Neuro-Genetic Approach to Hydraulic Fracture Treatment Design and Optimization*", Society of Petroleum Engineers Annual Technical Conference & Exhibition held in Denver, U.S.A., 6-9 October, 1996.

107. Pei-Yi H. and Jung-Hsien C., "*A Fuzzy Model of Support Vector Regression Machine", International Journal of Fuzzy Systems*", Vol. 9, No. 1, March 2007, Pp. 45 - 50.

108. Zeng J. and Zhi-Qiang L., "*Type-2 Fuzzy Hidden Markov Models to Phoneme Recognition*", IEEE Proceedings of the 17th International Conference on Pattern Recognition (ICPR), 2004.

109. Ehrenberg S.N., Eberli G.P. and Bracco G.L., “*Data report: Porosity and permeability of Miocene carbonate platforms on the Marion Plateau*”, Ocean Drilling Program Leg 194. *In* Anselmetti, F.S., Isern, A.R., Blum, P., and Betzler, C. (Eds.), *Proceedings of Ocean Drilling Program, Scientific Results,* 194, 2004 [Online]. Available from World Wide Web: <http://www-odp.tamu.edu/publications/194_SR/007/007.htm>

110. http://www.ncrg.aston.ac.uk/netlab