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A hybrid WFA approach for Short-Term Wind Power Forecasting

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Abstract

Wind generation is hectic by nature, making wind power forecasting highly challenging, particularly for short time frames. Forecasting of wind power is becoming progressively more important to power system operators and electricity market.Wind power is variable and irregular over various time-scales as it is weather dependent. Thus precise forecasting of wind power is acknowledged as a major contribution for reliable large-scale wind power assimilation. This proposed hybrid model is developed by combining techniques such as Wavelet Transformation (WT), Fireflies (FF) and Adaptive Network-based Fuzzy Inference System (or) Adaptive Neuro Fuzzy Inference System (ANFIS) to calculate wind power. Wind power forecasting is improved by taking advantage of each independent forecasting model.

INTRODUCTON

The Data Mining also called as knowledge discovery process is a technique of pulling out the valuable information and patterns from bulky set of data. It is often treated as the innate wing of the data warehousing concept. Data warehousing as a process to systematize the storage of large and multivariate data sets in a way that facilitates the retrieval of information for analytic purposes. Data mining techniques such as classification, clustering, prediction, association and sequential patterns helps in finding the patterns to decide upon the future trends in businesses to grow.

The wind is an open, hygienic, and infinite energy source. The motion of air is caused by differential heating of the earth's surface. Wind energy system converts kinetic energy in the atmosphere into electricity. Wind energy generation is expected to increase in future electric grids. Thus wind energy plays a larger role in providing electricity to industrial and domestic consumers.

Wind is affected by topography and wind speed is affected by roughness and obstacles such as buildings and hills. Wind speed is the rate at which air flows at a point above the earth's surface. Wind speed can be quite variable and is determined by a number of factors such as atmospheric pressure, moisture, humidity, rainfall etc.

Wind turbines are widely used for generating wind power in remote areas of high wind. They are considered an excellent alternative to diesel generators being environment friendly. Wind speed is very important parameter in energy conversion and management. Wind power is a grown-up renewable energy technology for electricity generation with high effectiveness and minimal pollution and greenhouse gas emissions. However, the increasing wind power breach level will affect the operation and reliability of the grid due to the flashing nature of wind generation. A reliable and accurate wind power forecasting is one of the most effective and economically possible solutions to this problem.

Forecasting is an important issue due to its effectiveness in human life to know what will happen for unpredictable situations and events. Forecasting of wind power generation is essential for optimum operation of a power system with a significant share of wind energy conversion systems. Wind forecasting can be based into three categories:

- Immediate-short-term (8hours-ahead) forecasting,
- Short-term (day-ahead) forecasting,
- Long-term (multiple-days-ahead) forecasting.

Wind forecasting schemes can also be classified based on their methodology into two categories:

➢ Physical approach:

Physical method or deterministic method is based on lower atmosphere or numerical weather prediction (NWP) using weather forecast data like temperature, pressure, surface roughness and obstacles. In general, wind speed obtained from the local meteorological service and transformed to the wind turbines at the wind farm is converted to wind power.

➢ Statistical approach:

Statistical method is based on vast amount of historical data without considering meteorological conditions. It usually involved artificial intelligence (neural networks, neuro-fuzzy networks) and time series analysis approaches.

- Hybrid approach:

Hybrid method which combines physical methods and statistical methods ， particularly uses weather forecasts and time series analysis.

In our proposed model forecasting of wind power calculation is done by using hybrid model. Here we have combined three independent algorithms Wavelet transformation (WT), adaptive-network-based fuzzy inference system (ANFIS), firefly (FF). Because occurrence of wind in nature is extremely uncertain no single technique can be entirely satisfactory. This leaves scope for alternative approaches.

2. EXISTING METHODS

"**Hybrid Wavelet-PSO-ANFIS Approach for Short-Term Wind Power Forecasting in Portugal**", is a novel hybrid approach for short-term wind power forecasting is based on the combination of wavelet transform (WT), particle swarm optimization (PSO), and adaptive-network-based fuzzy inference system (ANFIS). Our hybrid WPA approach is compared with persistence, NRM, ARIMA, NN, NNWT, NF, and wavelet-neuro-fuzzy (WNF) approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

The contributions of this paper are threefold:

1) To propose a novel hybrid approach for short-term wind power forecasting;

2) To improve forecasting accuracy, taking into account the results obtained with seven other approaches;

3) To offer a practical solution in terms of computational burden.

"**Wind Power Prediction by a New Forecast Engine Composed of Modified Hybrid Neural Network and Enhanced Particle Swarm Optimization**" a new wind power forecast strategy composed of an efficient two-stage feature selection technique and a novel forecasting engine. The presented feature selection technique can handle nonlinearities of a forecast process and filter out both irrelevant and redundant candidate inputs. Based on a minimum subset of the most informative selected features, the forecasting engine implements the input/output mapping function of wind power forecast process. Here the forecast engine is composed of MHNN and EPSO. MHNN, combining RBF and MLP networks, can capture both local and global behaviors of the target variable. By hybridizing MHNN with the enhanced stochastic search technique, i.e., the EPSO, the forecasting engine can benefit from good global search ability of the EPSO, avoiding being trapped in local minima, in addition to high convergence rate of the NN learning algorithms. Obtained results from extensive testing of the employed feature selection technique, the forecasting engine and the complete wind power forecasting strategy confirm the validity of the developed approach.

“A Hybrid Intelligent Model for Deterministic and Quintile Regression Approach for Probabilistic Wind Power Forecasting” a novel hybrid intelligent algorithm for deterministic wind power forecasts, the results of which are further evaluated by performing probabilistic forecasts using QR method. The innovative contribution of this paper is to develop an accurate, efficient, and robust deterministic WPF model using a combination of a data filtering approach based on wavelet transform (WT) and a soft computing model based on FA network, which is optimized using an optimization technique called firefly (FF) algorithm. The SVM classifier is also applied to minimize the WPF error. Here in after, the proposed hybrid deterministic model will be termed as WT+FA+FF+SVM in this paper. Then, the QR method is used for probabilistic forecasting. Finally, the forecasting performance of the deterministic hybrid model is compared with that of other soft computing and hybrid models (i.e., BPNN, FA, WT+BPNN, WT+FA, WT+BPNN+SVM, WT+FA+SVM, and the benchmark persistence” method) using wind power data from the Cedar Creek wind farm in Colorado. The comparison demonstrates a significant improvement in daily and weekly mean absolute percentage error (MAPE). The average MAPEs improvements by the proposed model over the other forecasting models for daily and weekly forecasts are around 53% and 38%, respectively. Furthermore, to evaluate the forecasting performance of the proposed hybrid intelligent WT+FA+FF+SVM deterministic model, it is also tested using wind power data from the Kent Hill wind farm in New Brunswick, Canada. This hybrid intelligent algorithm model reduced is MAPEs by around 27.5%, when compared with the deterministic approach. The test results of probabilistic forecasting also demonstrate the effectiveness of this proposed hybrid deterministic model.

“Hybrid Forecasting Model for Very-Short Term Wind Power Forecasting Based on Grey Relational Analysis and Wind Speed Distribution Features”, a hybrid forecasting model with the combination of LSSVM model and RBFNN model is proposed based on grey relational analysis and wind speed distribution features. The weight database is established according to different monthly wind speed segments. With this database, the forecasting process becomes simple. With the forecasting value of wind speed (obtained by numerical weather prediction) in every month, the weights of the two independent models can be extracted from the database. This approach can not only improve forecasting accuracy but also reduce computational burdens. From the results of the case study, it is shown that the MAPE and RMSE from the hybrid model are 2.37% and 3.79%, which are better than those in LSSVM and RBFNN.

3. PROPOSED METHOD

In this proposed hybrid model we use three different techniques Wavelet Transformation (WT), Fireflies (FF) and Adaptive Network-based Fuzzy Inference System (or) Adaptive Neuro Fuzzy Inference System (ANFIS) to increase the accuracy of forecasting result of the power generation. Our proposed model use

MATLAB 2013 as a tool where these algorithms are used one after another to produce better result on forecasting by giving a large amount of training and testing. As the occurrence of wind in nature is extremely uncertain no single technique usage can give satisfied result.

Wavelet Transform

The Wavelet Transforms (WT) have been recently developed as mathematical tools, based on a convolution operation between an original time series and an analyzing function, called wavelet or mother wavelet. In mathematics, a **wavelet series** is a representation of a square-integrable (real- or complex-valued) function by a certain orthonormal series generated by a wavelet. The WT becomes a powerful analyzing tool for stationary, non-stationary, intermittent time series, especially to find out hidden short events inside the time series. Because of its advantages, the WT have been applied in the various fields such as digital signal processing, image coding and compressing, numerical analysis and digital simulation, system and flow identification and so on, and they still are increasingly evolving.

In numerical analysis and functional analysis, a **discrete wavelet transform** (DWT) is any wavelet transform for which the wavelets are discretely sampled. The WT advantages over the conventional spectral transformations such as Fourier Transform (FT) and Short-Time Fourier Transform (STFT) in simultaneously time-frequency analysis with flexible resolutions. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

Fireflies

The firefly algorithm is a metaheuristic algorithm, inspired by the flashing behavior of fireflies. Firefly is an insect that mostly produces short and rhythmic flashes that produced by a process of bioluminescence. The function of the flashing light is to attract partners (communication) or attract potential prey and as a protective warning toward the predator. Thus, this intensity of light is the factor of the other fireflies to move toward the other firefly.

The primary purpose for a firefly's flash is to act as a signal system to attract other fireflies. The intensity (I) of flashes decreases as the distance (r) increases and thus most fireflies can communicate only up to several hundred meters. In the implementation of the proposed firefly algorithm, the flashing light is formulated in such a way that it gets associated with the objective function to be optimized.

In firefly algorithm, there are three idealized rules:

1. All fireflies are unisexual, so that one firefly will be attracted to all other fireflies;

2. Attractiveness is proportional to their brightness, and for any two fireflies, the less bright one will be attracted by (and thus move to) the brighter one; however, the brightness can decrease as their distance increases;
3. If there are no fireflies brighter than a given firefly, it will move randomly.

ANFIS

ANFIS, which stands for **adaptive network-based fuzzy inference system** or **adaptive neuro fuzzy inference system**. ANFIS is a hybrid of two intelligent system models. ANFIS is created from integration of fuzzy logic and neural network. This means that it is combining the best aspects of the two technologies, while limiting the drawbacks. The main objective of the ANFIS is to determine the optimum values of the equivalent fuzzy inference system parameters by applying a learning algorithm. The parameter optimization is done in such a way during the training session that the error between the target and the actual output is minimized.While designing of ANFIS model, it is extremely important that the number of training epochs, the number of membership functions and the number of fuzzy rules should be tuned accurately. A simple ANFIS "shell" can be developed using the "Matlab Fuzzy Toolbox". The easiest way to understand how the ANFIS model operates is to consider it in two steps. First, the system is trained in a similar way to a neural network with a large set of input data. Then, once trained, the system operates exactly as a fuzzy expert system. Figure1 shows the using model structure for our proposed model in MATLAB.

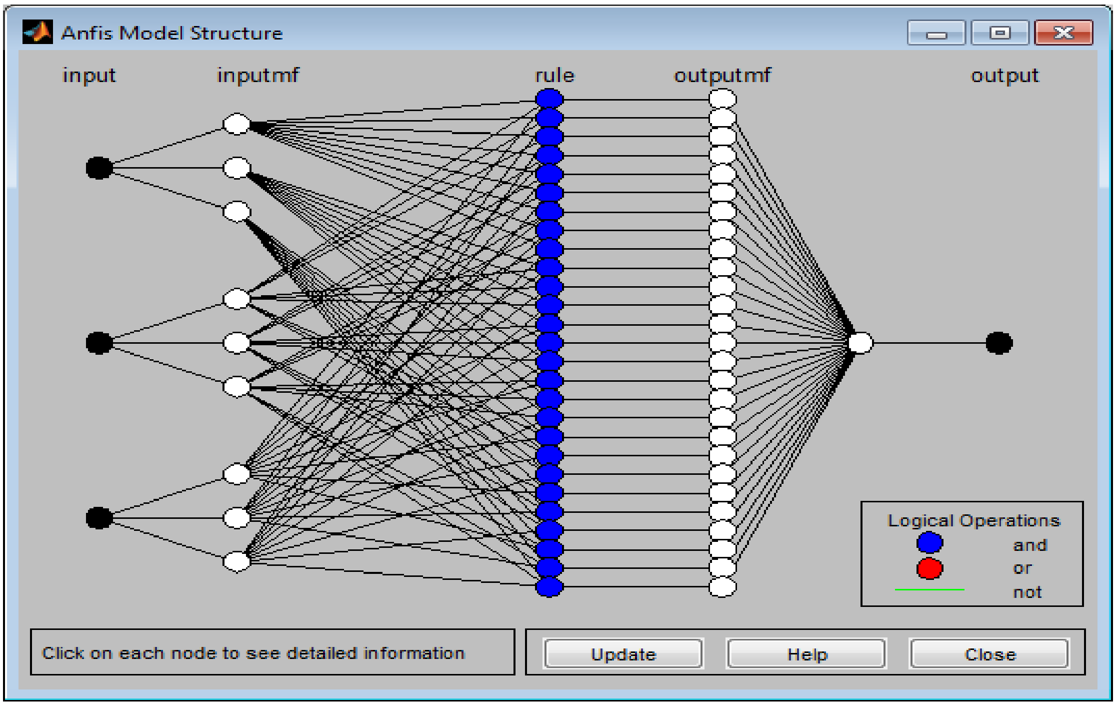


Figure 1: Anfis model

The specific advantages of ANFIS over the two parts of this hybrid system are:

- ANFIS uses the neural network's ability to classify data and find patterns.
- It then develops a fuzzy expert system that is more transparent to the user and also less likely to produce memorisation errors than a neural network.
- ANFIS keeps the advantages of a fuzzy expert system, while removing (or at least reducing) the need for an expert.

However, the problem with the ANFIS design is that a large amount of training data is required to develop an accurate system.

Our proposed model uses wind speed, velocity, swept area, air density, power coefficient, wind direction as the factor for power forecasting. Here the predicted speed value using the proficient adaboost BP algorithm is considered as wind speed (contain data of wind speed & wind direction) for the proposed model to calculate wind power.

The steps taken for wind power prediction in our proposed hybrid model are:

✓ **Discrete Wavelet Transform** (DWT) is applied on series of input data to remove noise and none values, then it compresses the data and captures the temporal resolution (frequency and location information).

✓ Fireflies is applied next to DWT for grouping high wind speed data.

✓ After grouping ANFIS is applied to convert original value to fuzzy value 0 and 1 in which year of high speed is seen.

✓

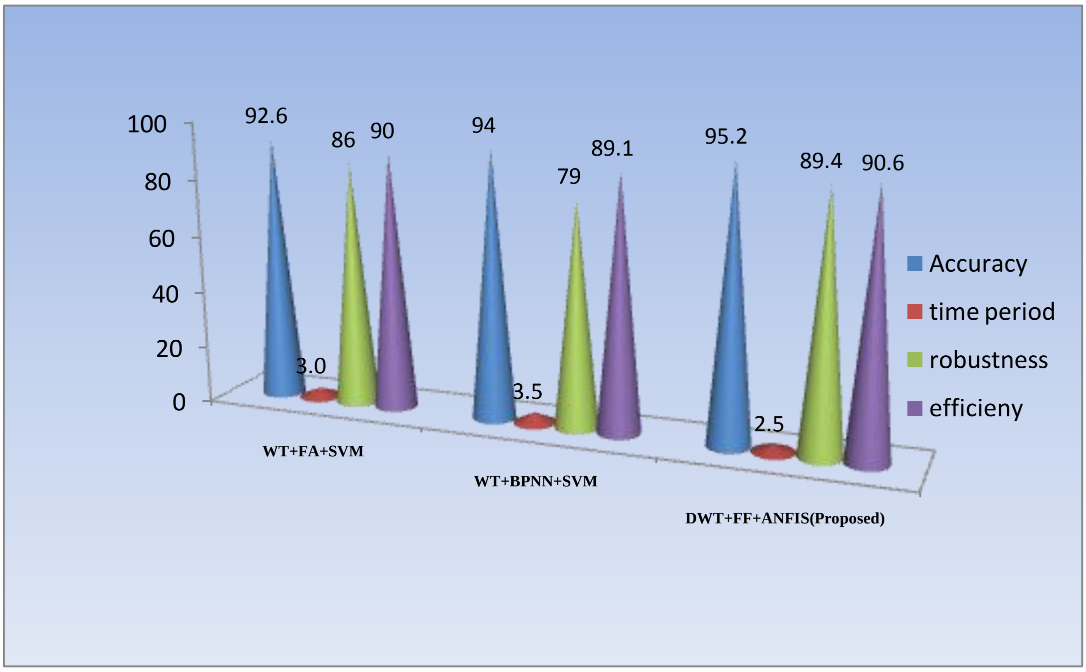


Figure 2: Comparition of proposed model with some existing

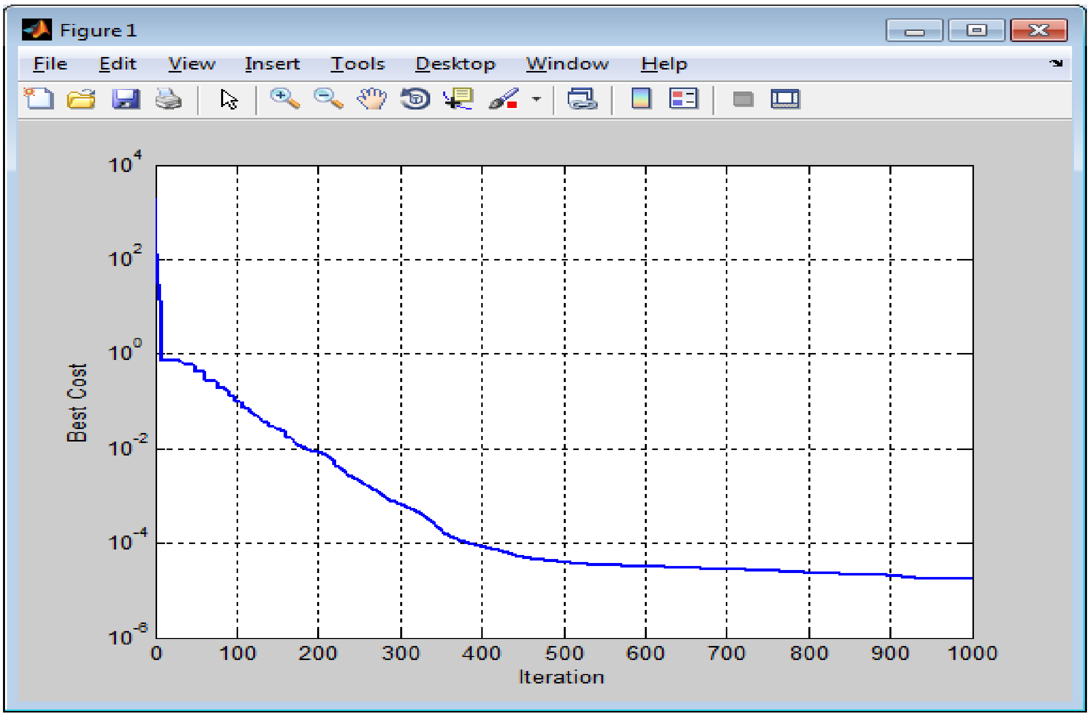
Large amount of training is given on data to get more accurate data. When compared to other hybrid method our proposed method produce better power forecasting result. Figure 2 shows the comparition of our proposed model with the existing model. This proves how our proposed hybrid model is improved than the other two by efficiency, accuracy, robustness and time period.

4. RESULT AND DISCUSSIONS

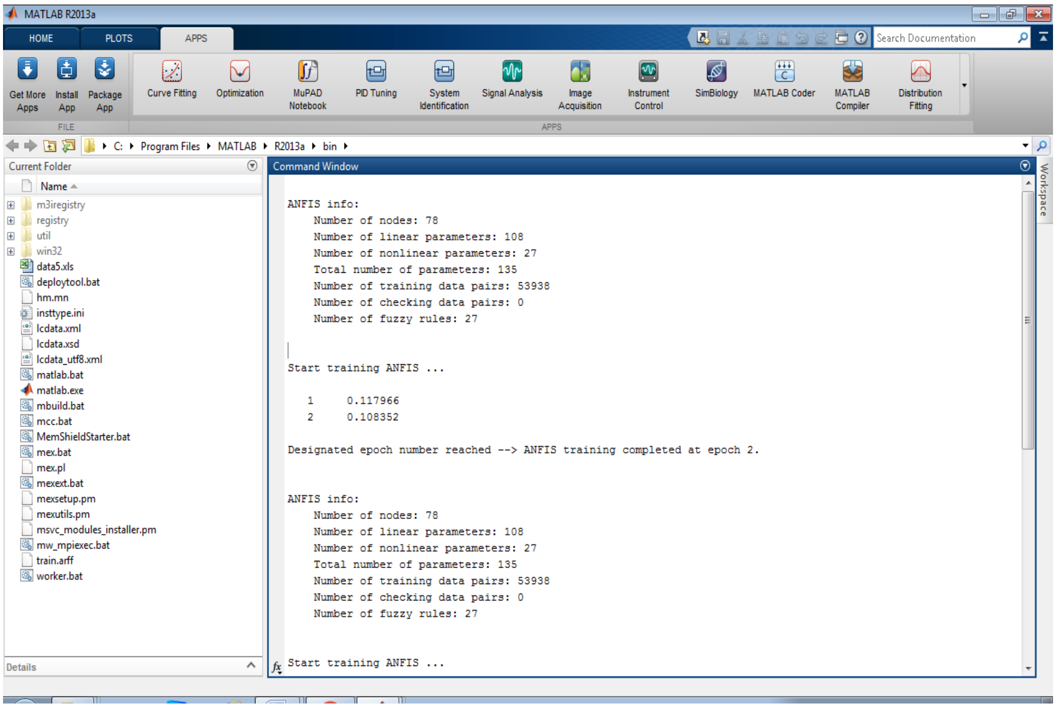
Our proposed hybrid model use three different techniques Wavelet Transformation (WT), Fireflies (FF) and Adaptive Network-based Fuzzy Inference System (or) Adaptive Neuro Fuzzy Inference System (ANFIS) to increase the accuracy of forecasting result of the power generation. Here these algorithms are used one after another to produce better result on forecasting. Our proposed hybrid model use wind speed, velocity, swept area, air density, power coefficient, wind direction as the factor for power forecasting. In future turbine height and blade length can also be used as a factor to generate accurate power in particular area.

Some of the screenshots of Matlab are shown below:

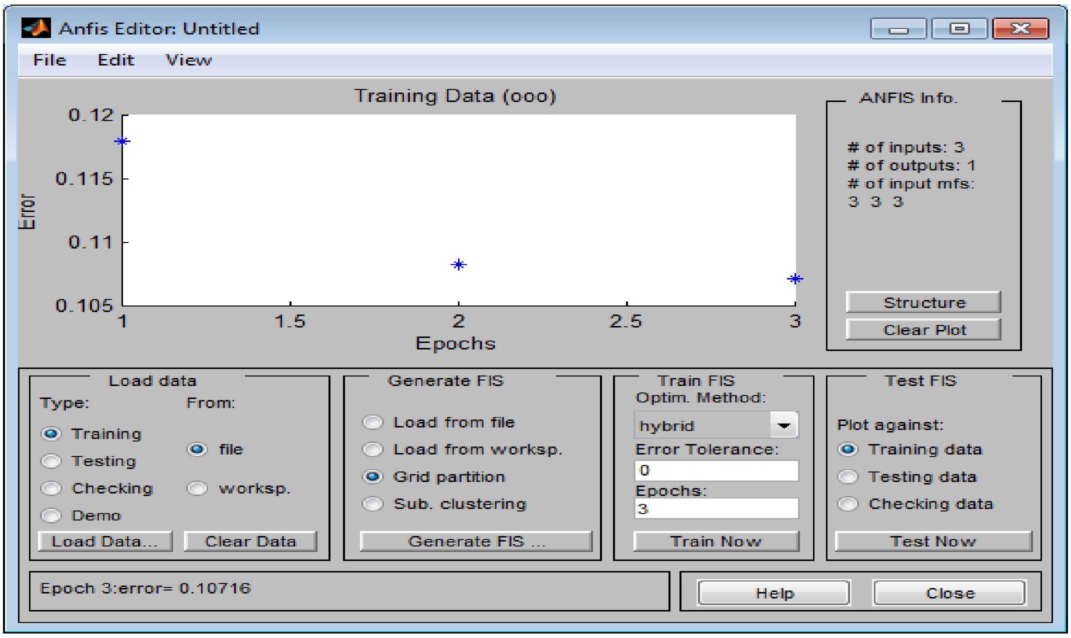
Firefly algorithm :



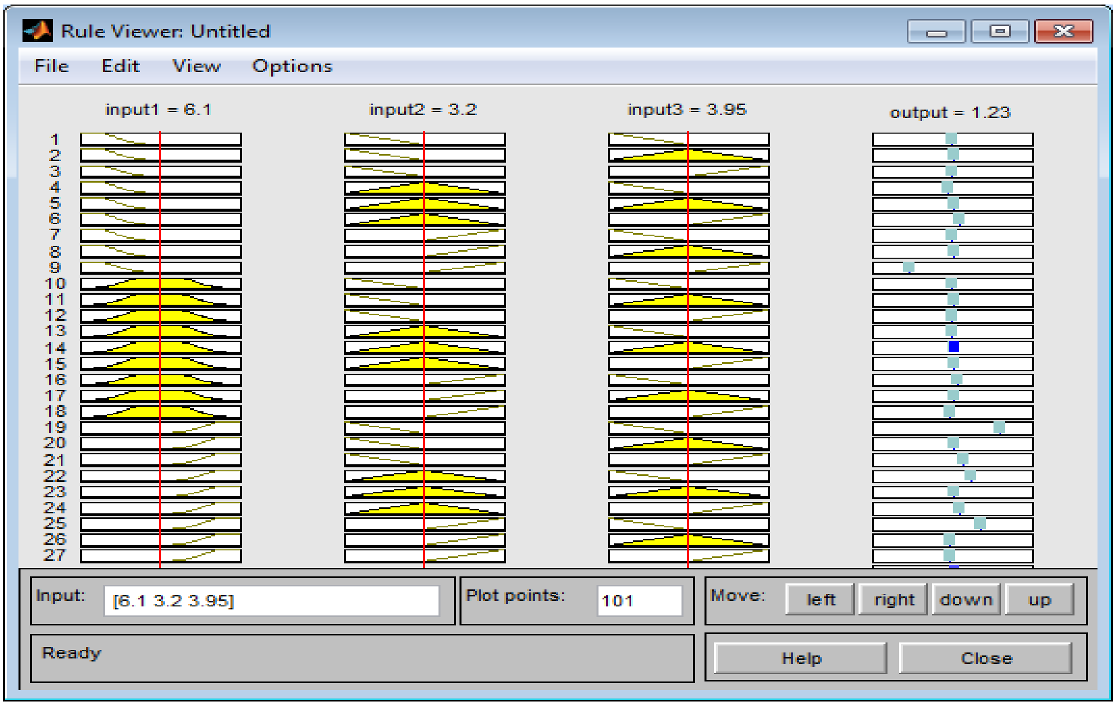
Generating anfis method:



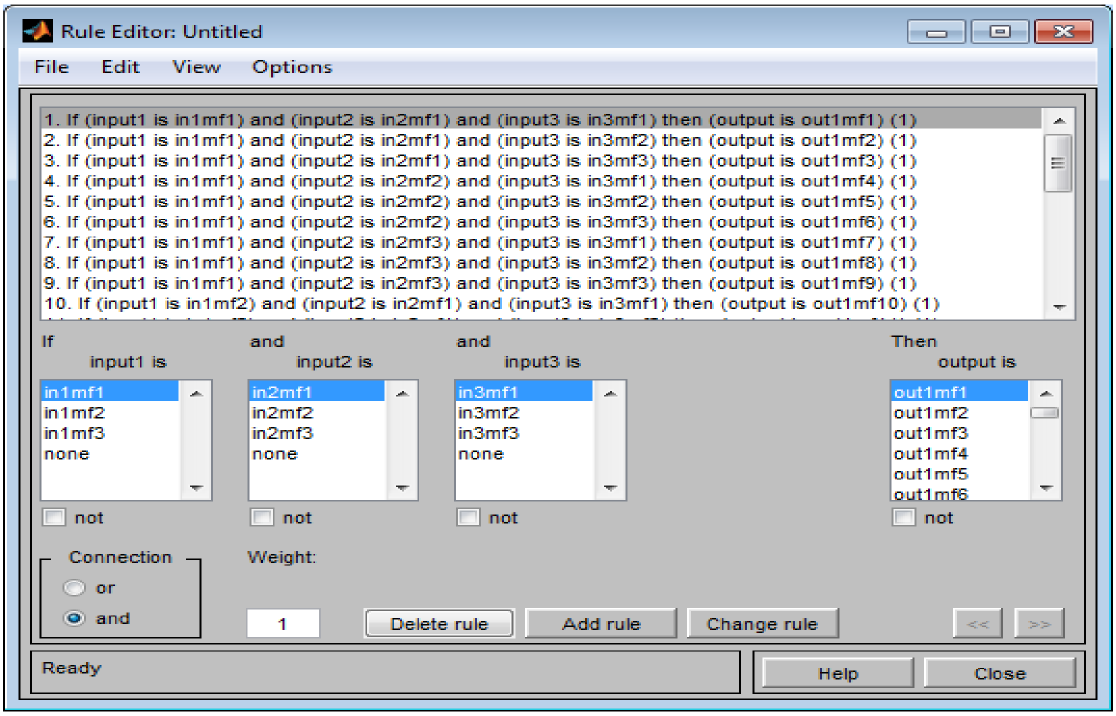
Anfis training:



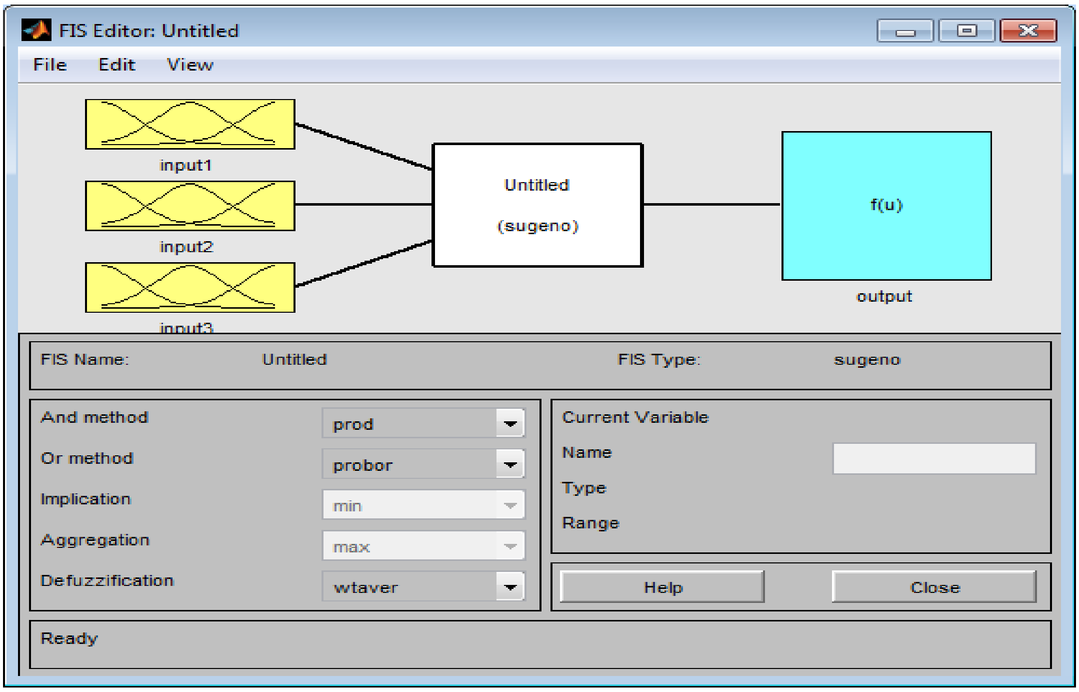
Rule viewer:



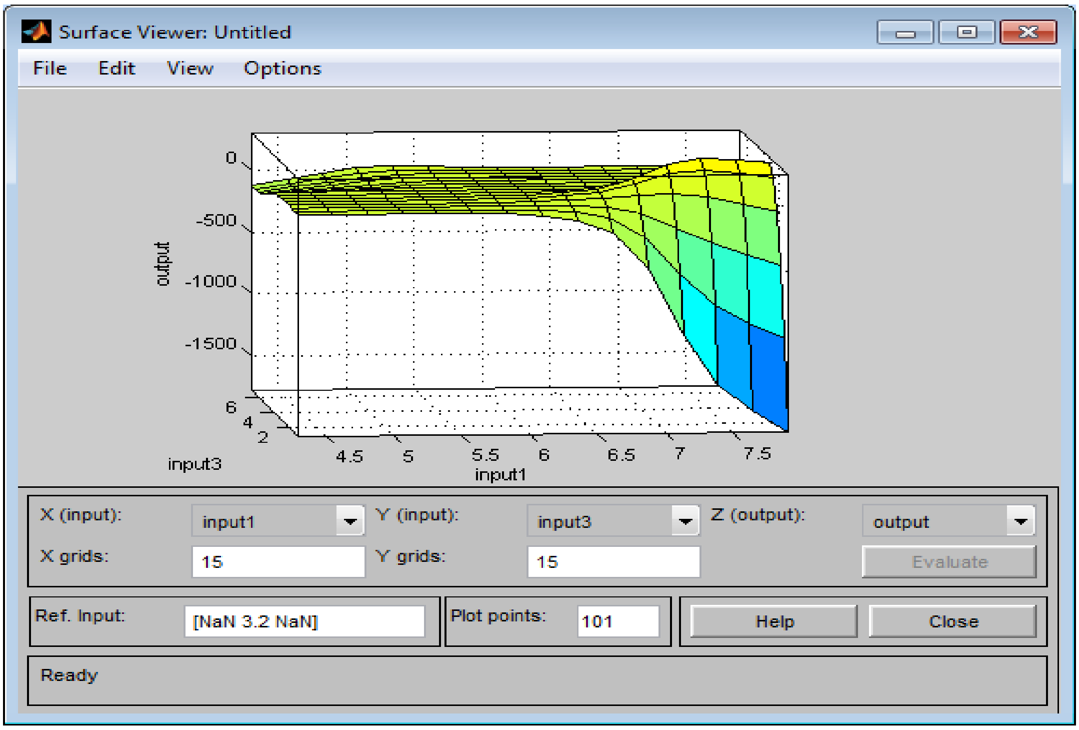
Rule Editor:



ANFIS editor:



Surface viewer:



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