Adaptive intelligent hydro turbine speed identification with water and random load disturbances

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Abstract

In this paper, the hydro power plant model (with penstock-wall elasticity and compressible water column effect) is simulated at random load disturbance variation with output as turbine speed for random gate position as input. The multilayer perceptron neural network (i.e. NNARX) and fused neural network and fuzzy inference system (i.e. ANFIS) for identification of turbine speed as output variable are reported. Emphasis is put on obtaining a generalized model, using (i) NNARX model and (ii) ANFIS model with membership functions defined by subtractive clustering for plant model representation under different values of water time constant. The comparative performance study between the two approaches is also addressed. In the end of the paper, an application of adaptive noise cancellation based on ANFIS model to identify the turbine speed dynamics is also discussed.

Keywords: Hydro power; Modeling; Adaptive; Neuro-fuzzy; Noise cancellation

1. Introduction

The response of power plant due to the variation in load is directly influenced by the performance of its governor, the stiffness of the connected system and the interaction between the governors. The frequency of the power system depends on the active power imbalance between the generator and the connected system. Small isolated autonomous power systems are particularly sensitive to disturbances, i.e., represent a relatively weak system. Thus any changes in the power input or output of one component may affect the rest of the system more drastically than an interconnected system.

The hydro turbine performance is largely determined by the characteristics of the water column effect in the penstock. These include the effects of water inertia, water compressibility and penstock-wall elastic properties. Due to water inertia the turbine flow lags behind the turbine gate opening. That is the turbine exhibits an initial inverse response characteristics. Again the elastic nature of penstock-wall leads to rise of traveling waves and thus the water hammer phenomenon. Briefly, it may be said that the operation of hydro turbine is both complex and inherently highly nonlinear with dynamic characteristics that vary with operating points. In conventional approaches, modeling and control prove to be inefficient under such conditions. In many applications, a detailed hydraulic system model is required to take into consideration the water column compressibility and penstock-wall elasticity properties. These effects are represented by a delay; $e^{-2T}$, in the hydraulic structure, which is irrational (Sanathanan, 1987). As a result nonlinear dynamic interaction between the hydraulic and the electrical system is introduced.

Mahmoud et al. (2005) extensively discussed the need for the development of accurate model of turbine and its controller design and henceforth they are not repeated here in the paper.

Fangtong et al. (1995) discussed open loop and closed loop identification of hydro turbine using recursive least-squares estimation algorithm. The dynamic modeling of hydro turbine generating set as a single machine with local
load using recursive least-squares estimation algorithm is already discussed in Qijuan and Zhihuai (2000). Also a neural network structure 3-2-1 using recursive prediction error-learning algorithm is presented for modeling of turbine/generator (Chang et al., 1996). The nonlinear simulation of hydro turbine governing system based on neural networks (NNs) is also described in the said paper. In the study two three-layered perceptron NN1 and NN2 of structure 1-4-1 and 2-12-2 are considered. The former structure forms a nonlinear relation between servomotor stroke and guide vane opening while later structure between guide vane, speed efficiency and discharge.

In Djukanović et al. (1997), ANFIS-based nonlinear, multivariable control for the exciter and the governor loop in a low-head hydro power plant is presented. The plant is connected as a single machine infinite bus system. The controller is designed using the back-propagation type gradient descent method called “temporal back propagation”. The comparison between the fuzzy inference system (FIS) governor and PID controller in a pumped storage hydro plant is discussed in King et al. (2001). An excellent response to a step increase in load is shown by FIS than PID-based controller. The penstock effect dynamics have been considered to be negligible.

Many of the authors have not considered the investigations that include the dynamics in long penstock. The study made for relatively long penstock on the basis of inelastic water column effect will have significant error. Such approach in the governor design downgrades the assessment of controller effectiveness. The development of plant model provides a better insight of plant characteristics and to understand the physical phenomenon. In hydro power plant model development related to physical and design data, sometimes the accurate data needed for calculation of model parameter may be difficult. In some literatures (Chawdhry and Hogg, 1989; Pellegrinetti and Bentsman, 1996), such models have been used as a basis to identify a corresponding model through identification techniques. Methods based on NNs (i.e. black-box model) and ANFIS (i.e. grey-box model) do not need an exact mathematical model of the system and possess high degree of non-linearity. Both the methods have been shown to possess the capability of modifying complex nonlinear processes to the arbitrary degree of accuracy. In recent publications (Kishor et al., 2005, 2006; Kishor and Singh, 2007a,b), NNs-based method (i.e. NNARX model) has been successfully shown to represent the hydro plant dynamics. The developed model considered the input as random gate position and the output as turbine power/deviated power.

In this paper, it is more emphasized to develop a generalized knowledge-based model of the hydro plant. The model is represented as single-input and single-output system with input as random gate position and output as turbine/generator speed on random load disturbance. The hydro plant with speed as output is identified using NN nonlinear auto-regressive with exogenous signal (NNARX) and adaptive neuro-FIS (ANFIS). These two approaches are compared in plant dynamics representation. Also adaptive noise cancellation (ANC) based on ANFIS model has been considered in the study.

2. Hydro turbine dynamics

A general arrangement of hydraulic structures and components in a hydro power plant is shown in Fig. 1. It has a simple layout consisting of a reservoir, a tunnel (low pressure), a surge tank, a penstock (high pressure), a wicket gate, a Kaplan hydro turbine and a generator. Water from the reservoir enters the tunnel and then through the penstock into the scroll casing of turbine. The scroll casing evenly distributes the water on the runner blades. And the runner transfers the developed mechanical power to the electric generator (electro-mechanical conversion) being mounted on a common shaft with it. The flow of water into
turbine is regulated by means of wicket gates (with operation of governor), as a function of variable electrical load connected to generator.

The dynamic equations of hydraulic and mechanical/electrical systems in power plant are described as follows (Kishor and Singh, 2007b; Quiroga, 2000).

2.1. Dynamics of tunnel

Frictional loss in the tunnel is proportional to the square of the flow rate. Water flowing through the tunnel experiences frictional forces, which cause a loss of head proportional to the square of the flow rate:

\[ \bar{H}_{\text{tunnel}} = f_{\text{tunnel}} \bar{U}_{\text{tunnel}} | \bar{U}_{\text{tunnel}} |. \]  

The dynamics of head variation in tunnel is:

\[ \bar{H}_{\text{devia, tunnel}} = -T_{\text{wi}} \frac{d\bar{U}_{\text{tunnel}}}{dt}. \]  

2.2. Dynamics of surge tank

The riser in surge tank helps to suppress water hammer that occurs on rapid change in the turbine gate position. The head rise in riser on rapid closure of turbine gate is

\[ \bar{H}_{\text{riser}} = \bar{H}_0 - \bar{H}_{\text{tunnel}} - \bar{H}_{\text{devia, tunnel}} \]  

where \( \bar{H}_0 \) is the rated turbine head in p.u.

On rapid closure of turbine gates, the kinetic energy of flowing water in the penstock is converted into potential energy. This helps in release of pressure built-up. Also the head dynamics in the riser of surge tank is given as

\[ \bar{H}_{\text{riser}} = \frac{1}{C_{\text{surge}}} \int U_{\text{surge}} dt - f_0 C_{\text{surge}} | U_{\text{surge}} |, \]  

where \( C_{\text{surge}} \) is the storage constant of surge tank in s and \( f_0 \) is the head loss coefficient of riser.

2.3. Dynamics of penstock

The head loss due to water flowing in the penstock is written as:

\[ \bar{H}_{\text{penstock}} = f_{\text{penstock}} \bar{U}_{\text{turbine}}^2. \]

Assuming a uniform conduit length, the head deviation and turbine flow are related as

\[ \bar{H}_{\text{devia, penstock}} = -Z_p \tan h(T_{\text{penstock}}) \bar{U}_{\text{turbine}}, \]  

where \( Z_p \) is the hydraulic surge impedance of penstock (\( = T_w/T_{\text{penstock}} \)).

Thus the available head at the turbine inlet is

\[ \bar{H}_{\text{turbine}} = \bar{H}_{\text{riser}} - \bar{H}_{\text{penstock}} - \bar{H}_{\text{devia, penstock}} \]

2.4. Mechanical power

The developed turbine power is given by:

\[ \bar{P}_{\text{develop}} = A_{\text{gain}} \bar{H}_{\text{turbine}} (\bar{U}_{\text{turbine}} - \bar{U}_{\text{load}}) \]  

\[ \bar{P}_{\text{damping}} = D_{\text{turbine}} \bar{G}_{\text{open}} \Delta \bar{o}_r \]

where \( \bar{G}_{\text{open}} = \bar{U}_{\text{turbine}} / \sqrt{\bar{H}_{\text{turbine}}} \.

The term \( \bar{P}_{\text{damping}} \) represents the damping effect due to friction and it is proportional to the rotor speed deviation and the gate opening.

The deviated power that causes acceleration (or deceleration) is

\[ \bar{P}_{\text{dev}} = \bar{P}_{\text{develop}} - (\bar{P}_e + \bar{P}_{\text{damping}}), \]  

where \( \bar{P}_e \) is the power generated, sum of power consumed by the users and electrical losses.

Throughout the paper, the term \( \bar{P}_e \) is referred as “load disturbance”. The variation in deviated power describes the effect of unbalance between the changes in turbine power and load disturbance as given in swing equation:

\[ \bar{o}_r = \frac{1}{T_{ms}s + D_{\text{load}}} (\bar{P}_{\text{dev}}). \]  

It is understood from the Eq. (11) that any imbalance in deviated power \( \bar{P}_{\text{dev}} \) will cause either acceleration or deceleration of the generator/turbine according to the laws of motion of a rotating body. Eq. (11) describes the variation of turbine speed when the balance between developed power and load demand is no longer preserved, i.e. \( \bar{P}_{\text{develop}} \neq (\bar{P}_e + \bar{P}_{\text{damping}}) \).

3. Methodology in identification

This section describes the procedure to model a non-linear relationship between the speed and random variation in gate position. Fig. 2(a) shows the power plant representation as block diagram to generate input-output data for turbine speed identification. Neglecting the damping coefficient, the dynamic model given by Eqs. (1)–(11) is solved on digital computer to simulate the plant response and generate the identification data at a rated water time constant \( T_w \) with plant parameters as given in Appendix.

To simulate the turbine model with load variation, a signal \( P_e \) is generated representing pseudorandom binary signal (Eker, 2004) with a variance of 0.005, which is again...
superimposed on a signal obtained by integrating another random signal of variance 0.01 as shown in Fig. 2(b). The random variation in gate position represented by pseudorandom binary signal is fed to the input. And the corresponding simulated turbine/generator speed data is collected at a sample rate of 0.09 s. Thus the plant considered in study is a single-input, single-output, being subjected to random load variation. The objective is to model hydro plant using NNARX and ANFIS methods. Though off-line identification has disadvantage of requiring large amount of data to store, but its merit in reduced training time and improvement in generalization (Saint et al., 1991) has forced to use the same for model identification.

4. Turbine speed NNARX model identification

The hydro plant can be represented in discrete input and output form by the identification structure:

\[ y(k, \theta) = f_{\text{NN}}(\Phi(k, \theta)) + \xi(k), \]  

(12)

where \( f_{\text{NN}} \) is the function realized by the NN; \( \theta \), the model parameter(s) (the weights); \( \xi(k) \), the additive noise which is assumed to be white noise or model residual.

The NNARX regression vector is expressed as

\[ \Phi(k) = [y(k-1), \ldots, y(k-n_y), u(k-n_u), \ldots, u(k-n_u-n_k-1)]^T, \]  

(13)

where \( n_u, n_k \) is the past output and input data sample(s) of the plant to be controlled at time \( k \); \( n_k \), the delay in the input signal, and let \( m = [n_u, n_k] \): NNARX model structure dimension.

As a measure to select the “best” model structure among the various possibilities, a widely used identification cost function (ICF), being the sum of square error given by (Nørgaard et al., 2000)

\[ V_N(\theta, Z_N^2) = \frac{1}{2N} \sum_{t=1}^{N} [y(t) - \hat{y}(t|\theta)]^2 \]

\[ = \frac{1}{2N} \sum_{t=1}^{N} \xi^2(t|\theta) \]  

(14)

is used. An optimization technique called Levenberg–Marquardt method (Nørgaard et al., 2000) is used to train the NNs, i.e. for minimization of mean-square error (MSE) criteria \( V_N \). This method is faster for training moderate-sized feedforward NNs and more powerful in computation than gradient descent back-propagation training method (Jurado et al., 2002).

During network training, the hidden layer weights are initialized automatically. With the learning rate \( \eta = 1 \times 10^{-4} \) and the momentum coefficient \( \zeta = 0 \), the network training is terminated when either the maximum error gradient is less than \( 1 \times 10^{-4} \) or the number of iteration exceeds 500. The NN model representation has a great difficulty in selection of appropriate model order. To select an optimum NN structure, the influence of variation in the number of past input data, past output data and hidden layer neurons (HLNs) on cost function is studied.

4.1. Optimal network structure

To determine an optimum NNARX structure, the influence of number of past input data, past output data
and HLNs on cost function is analyzed at rated water time constant $T_w$. With a large set of data sample collected through simulation, input–output samples corresponding to region R-1 of load disturbance is used to train the NNARX model and data sample corresponding to region R-5 to validate the model.

The initial configuration is assumed oversized; comprising 10 past input and 10 past output data sample in the regression vector. The hyperbolic tangent and linear activation function is used in HLNs and output layer neuron, respectively. Keeping the number of neuron in output layer as one and the number of neuron in hidden layer is varied in each step to study the influence of HLNs on cost function. The detailed steps involved in NNARX model identification with output variable as turbine power/deviated power has been discussed in [Kishor and Singh, 2007a,b; Kishor et al., 2006]. Based on this approach, the final model is selected after validation through high-order cross-correlation, auto-correlation (Billings and Voon, 2007a,b; Kishor et al., 2006) and mean-squared test on validation test data. Thus the NNARX model structure so identified consists of 18 inputs; three past speed samples, 15 past gate position samples and one hidden layer with 15 neurons as shown in Fig. 3.

To assess generalization of identified model at water disturbance, the above-identified structure is simulated for different values of $T_w$. The qualitative representation of the model is shown in Fig. 4. For variation in water time constant upto $T_w = 60\%$, there exists a close variation (i.e. error less than 0.005) between the response of dynamic model and identified NNARX model. However, for $T_w = 40\%$ and $20\%$ during the initial stage of simulation, there exists an appreciable error between the two responses. Thus it is understood that an accurate NNARX model is described upto $T_w = 60\%$.

5. Turbine speed ANFIS model identification

In the previous section, NNs are demonstrated to have powerful capability of expressing relationship between input–output variables. In fact they constitute a powerful interpolation tool and it is always possible to develop a structure that approximate a function with a given precision. However, there is still distrust about the NNs identification capability in some applications (Castro and Miranda, 2002). A NN although can approximate a function, but fails to interpret the result due to concept of black box in modeling. These networks do not have capability to explain about the system.

Fuzzy set theory plays an important role in dealing with uncertainty in plant modeling applications. Neuro-fuzzy (NF) systems are fuzzy systems, which use NNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples (Mitra and Hayashi, 2000). NF integrates to synthesize the merits of both NN and fuzzy systems in a complementary way to overcome their disadvantage. The fusion of NN and fuzzy logic in NF models possess both low-level learning and computational power of NNs and advantages of high-level human like thinking of fuzzy systems. For identification, hybrid NF system called ANFIS combines a NN and a fuzzy system together. ANFIS has been proved to have significant results in modeling nonlinear functions. In ANFIS, the membership functions (MF) are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to given error criterion. In a fused architecture, NN learning algorithms are used to determine the parameters of FIS. Fused NF systems change data structures and knowledge representations.

5.1. ANFIS methodology

ANFIS is a method for tuning an existing rule base with a learning algorithm based on the collection of training data. This allows the rule base to be adaptive. For illustration, consider the FIS has two inputs $u_1$ and $u_2$, one output $y$, and the rule base contains two fuzzy If–then rules of first-order Takagi–Sugeno type:

Rule 1:

If $u_1$ is $A_1$ and $u_2$ is $B_1$ then $y_1 = p_{11}u_1 + q_{11}u_2 + r_1$,  

Rule 2:

If $u_1$ is $A_2$ and $u_2$ is $B_2$ then $y_2 = p_{21}u_1 + q_{21}u_2 + r_2$,  

where $u_1$ and $u_2$ are inputs, $A_i$ and $B_i$ are fuzzy sets, $y_1$ and $y_2$ are the outputs within the fuzzy region specified by the fuzzy rule, $p_{ij}, q_{ij}, r_i$ are the design parameters to be determined during training stage, also called as consequent parameters. These rules are implemented in structure form as discussed in next section.

![Fig. 3. Multilayer perceptron NN model structure for turbine speed identification.](image-url)
Fig. 4. Dynamic model and NNARX model response for different values of water time constant i.e. at water disturbance. Dotted—NNARX model output; solid line—Dynamic model output.
5.2. Network representation of fuzzy system

ANFIS implements a Takagi–Sugeno FIS (Jang et al., 1997) and has a five-layered architecture as shown in Fig. 5.

The layer 1 (fuzzification layer) is adaptive as the output of each node depends on the parameters pertaining to these nodes. \( A_i \) and \( B_i \) can be any appropriate fuzzy sets in parameter form. The bell-shaped MF is quite popular for specifying fuzzy sets as they are nonlinear and smooth and their derivatives are continuous. This function is specified as

\[
\mu_{A_i}(u_t) = \frac{1}{1 + \left\{(u_t - c_i)/a_i\right\}^2},
\]

(17)

where \( a_i, b_i \) and \( c_i \) are the parameters of the MF and their values lead to change the shape of the MF. The parameters in this layer are called premise parameters.

The output of node \( i \) in this layer is given as

\[
O^1_i = \mu_{A_i}(u_t) \quad i = 1, n,
\]

(18)

\[
O^1_j = \mu_{B_{j-2}}(u_n).
\]

(19)

\( O^1_i \) denotes the output of the \( i \)th node in \( j \)th layer.

Layer 2 is the inference layer and each node is fixed and represents the \( If \) part of a fuzzy rule. Each node estimates the firing strength \( (w_i) \) of the rule. This layer aggregates the membership grades using any fuzzy intersection operator which can perform fuzzy AND operation. The output of \( i \)th node is given as

\[
O^2_i = w_i = \mu_{A_i}(u_t)\mu_{B_i}(u_n) \quad i = 1, n.
\]

(20)

The output of each node in this layer represents the firing strength of the rule.

In layer 3 (normalization layer) the \( i \)th node remains fixed and performs the normalization of the firing strength from the second layer. The output of each node is given as

\[
O^3_i = \bar{w}_i = \frac{w_i}{w_1 + w_2} = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad i = 1, n.
\]

(21)

\[
\text{Forward pass}
\]

\[
\text{Backward pass}
\]

Fig. 5. ANFIS model 5-layered structure architecture.

The layer 4 (output layer) represents the \( then \) part of fuzzy rule. Each node is adaptive node. The output of each node is simply the product of the normalized firing strength and is a first order polynomial given as

\[
O^4_i = \bar{w}_iy_i = \bar{w}_i(p_iu_t + q_iu_n + r_i) \quad i = 1, n,
\]

(22)

where, \( \{p_i, q_i, r_i\} \) is the parameter set of the node \( i \), referred as consequent parameter.

The layer 5 (defuzzification layer) performs the sum to produce a crisp output. The output of single node in this layer is given as

\[
O^5_i = y = \sum_i \bar{w}_iy_i = \frac{\sum_i w_i^o y_i}{\sum_i w_i^o} \quad i = 1, n,
\]

(23)

which is a linear combination of consequent parameters.

5.3. The ANFIS learning algorithm

Given an initial fuzzy system and input–output training data patterns, the main objective of training algorithm is to tune all the modifiable parameters \( \{a_i, b_i, c_i\} \) and \( \{p_i, q_i, r_i\} \) of the MFs in the nodes of layer 1 and the coefficients in the neural units of layer 4, respectively, so that ANFIS output exactly matches the training data. The ANFIS model is trained either using back-propagation learning algorithm or hybrid learning rule. Back-propagation is an error-based supervised learning algorithm, which is generally slow and likely to get trapped in local minima. However, the hybrid-learning rule is a combination of gradient descent method and least-squares estimation (LSE) and hence used in the study. It relatively converges faster. Each epoch during learning takes place in two phases: forward pass and backward pass. In Takagi–Sugeno’s fuzzy \( If–Then \) rules, the consequent rules are linear. The training data pair \( P \) supplied into input layer in matrix equation form as (Himer et al., 2004)

\[
AX = B,
\]

(24)

where \( X \) is an unknown vector whose elements are consequent parameters. A least square estimation of \( X \), \( X^* \) is obtained to minimize the square error \( \|AX - B\|^2 \). The well-known formula for \( X^* \) uses the pseudo-inverse of \( A^* \):

\[
X^* = (A^*A)^{-1}A^*B,
\]

(25)

where \( A^* \) is the transpose of \( A \), and \( (A^*A)^{-1}A^* \) is the pseudo-inverse of \( A \).

In the forward pass the training data is supplied at input layer and the functional signals move forward to calculate each node output until the matrix \( A \) and \( B \) in Eqs. (24) and (25) is computed. The nonlinear parameters in the fuzzy sets remain fixed and the linear parameters in the consequent functions are estimated by least-squares method. The output of layer 5 is compared with the actual output and the error measure is calculated as

\[
E_T = \frac{1}{2}(T_p - O^5)^2,
\]

(26)
where $T_P$ is the actual or target output and $O^5$ the single node output of defuzzification layer i.e. layer 5.

In the backward pass, error rates propagate backward from the output end towards the input end and nonlinear parameters i.e. premise parameters in layer 1 are updated according to gradient descent method.

The MATLAB® (2004) toolbox function Genfis2 performs cluster analysis in order to generate fuzzy sets due to projections of clusters in the multidimensional space onto the corresponding axis. This function uses the subtractive clustering algorithm to determine the number of rules and antecedent MFs and then uses global linear LSE to determine each rule's consequent equations.

### 5.4. ANFIS training and validation

The rules are acquired using subtractive clustering algorithm and then the ANFIS model is trained on input–output data sample corresponding to region, R-1 to R-6 of load disturbance at rated $T_w$. The ANFIS model is verified on the validation data set different from training data set so that it emulates behavior of the speed signal. To validate accuracy of the ANFIS model, it is compared graphically and numerically with behavior of the plant model, when subjected to identical input. In the present work, comparison is made on the basis of standard deviation, trained RMSE and validated RMSE performance. The model generalization property is tested with training on data sample collected at $T_w = 20\%$.

Table 1 shows the computed root mean square error (RMSE) values on the training data and validation data. The observation from the said table suggests a poor fit of the function with FIS obtained by subtractive clustering. However, the numerical performance in terms of RMSE has improved using ANFIS method with rules generated by subtractive clustering i.e. a satisfactory fit of the function is obtained.

The comparative speed error (i.e., difference between dynamic model response and predicted response) response between the NNARX and ANFIS model for region R-1 and R-6 is shown in Fig. 6. From Fig. 6(a) it is noted that speed error of NNARX model at rated $T_w$ is poor in initial stage and converges to zero at a later stage for region R-6, which has not been used in training of model. However, the speed error of NNARX model for region R-1 for which it has been trained varies along the zero-scale (i.e. zero mean value). Also the same varies along zero-scale for ANFIS model. It is noted that, the performance of the said response obtained for ANFIS model remains unchanged even for region R-6. A similar variation of speed error is observed in Fig. 6(b) when simulated at $T_w = 20\%$, except the fact that the speed error for ANFIS model in region R-1 and R-6 overlaps each other on zero-scale, while that of NNARX model in region R-1 varies along zero-scale.

Fig. 7 demonstrates the speed error for different values of $T_w$ in region R-1. A relatively closer identification of speed dynamics is observed by ANFIS model irrespective of percentage of water time constant since the speed error varies along the zero-scale of the graph.

Table 2 presents the ability to preserve statistical attributes of the speed error signal, i.e. difference between dynamic and its identified model response. The relative comparison of standard deviation and mean of speed error signal for randomly chosen regions, R-1 and R-6 with different values of water time constant are presented. It is suggested that the ANFIS model for turbine speed identification yields better dynamic response as compared to NNARX model.

### 6. ANC modeling

Like many other signals, noise too corrupts the speed signal. Nonlinear behavior, plant disturbance, sensor noise and modeling errors invariably lead to deviation from the true state. ANC is an approach to reduce the presence of noise effect based on reference noise signals (Widrow and Glover, 1975). The purpose is to adaptively model the nonlinear relationship between a measurable noise source and its corresponding unmeasurable interference using an ANFIS model. Fig. 8 shows the scheme of ANC to...
estimate speed signal $\hat{s}_p(k)$ when the same is corrupted with noise source signal $n_{os}(k)$ through some unknown dynamic. The distorted signal (i.e. interference signal) $d_{s}(k)$ is generated from the noise source through an unknown nonlinear dynamics known as passage dynamics. This signal is added to information speed signal $s_p(k)$ to form the measurable output signal $y_{os}(k)$. Here $\hat{d}_s(k)$ denotes the output of ANFIS and $s_p(k)$ is the output of whole system. Assume that information signal (IS) $s_p(k)$ is not correlated with $n_{os}(k)$, $d_{s}(k)$ and $\hat{d}_s(k)$.

The measurable output signal $y_{os}(k)$ is

$$y_{os}(k) = s_p(k) + d_{s}(k) = s_p(k) + f_s(n_{os}(k), n_{os}(k-1), n_{os}(k-2), \ldots).$$  

(27)

The function $f_s(\cdot)$ represents the passage dynamics that the noise signal $n_{os}(k)$ passes through. The aim is to retrieve the speed signal $\hat{s}_p(k)$ from the measurable output signal $y_{os}(k)$. If $f_s(\cdot)$ were known exactly, it would be easy to recover the original speed signal $s_p(k)$. However, $f_s(\cdot)$ is usually not known in advance and could said to be time-varying. Since it is assumed that $s_p(k)$ is zero mean and not correlated with the noise source $n_{os}(k)$, the measurable output signal $y_{os}(k)$ can be as a desired output of ANFIS model training. The learning rule of ANFIS model tries to minimize the error (Yin et al., 2004):

$$|e(k)|^2 = |y_{os}(k) - \hat{d}_s(k)|^2,$$  

(28)

$$|e(k)|^2 = |s_p(k) + d_{s}(k) - \hat{d}_s(k)|^2,$$  

(29)

$$|e(k)|^2 = |s_p(k) + d_{s}(k) - \hat{f}_s(s_p(k), s_p(k-1), s_p(k-2), \ldots)|^2,$$  

(30)

where $\hat{f}_s(\cdot)$ is the function of ANFIS model.
Expansion of Eq. (29) gives
\[ e(k) = |s_p(k)|^2 + |d_s(k) - \hat{d}_s(k)|^2 + 2s_p(k)d_s(k) \]

Taking expectation from both sides of Eq. (31) and according to the assumption that \( s_p(k) \) is not correlated with \( d_s(k) \) and \( \hat{d}_s(k) \) gives
\[ E[e^2] = E[s_p^2] + E[(d_s - \hat{d}_s)^2]. \] (32)

The signal power \( E[s_p^2] \) is not influenced when ANFIS is adjusted to minimize \( E[e^2] \). The ANFIS output \( \hat{d}_s(k) \) is the best square estimate of the \( d_s(k) \), and the function achieved by ANFIS can be as close as the passage dynamics \( f_s(\cdot) \) in a LSE of the speed signal, i.e.
\[ \hat{s}_p(k) - s_p(k) = d_s(k) - \hat{d}_s(k). \] (33)

Therefore, training of ANFIS is to minimize the total error \( E[e^2] \), which is equivalent to minimizing \( E[(d_s - \hat{d}_s)^2] \).

The MF in the ANFIS can be any approximate parameterized MF, such as the bell MF. The training of ANFIS is to adjust the MF parameter using a combination of least-squares and the back-propagation gradient descent method so that the ANFIS output well approximate the unknown distorted signal.

To perform the ANC without cluster of data, the model is trained with 1000 training data samples and is validated with another different 1000 data samples. Fig. 9 shows the simulated speed signal, noise source, distorted noise signal and measurable output signal. The convergence of RMSE as a function of epoch (i.e. iteration) for various number of MFs at rated \( T_w \) is shown in Fig. 10(a) and the corresponding step size variation is shown in Fig. 10(b). A true convergence (i.e. with both linear and nonlinear parameters) is shown for a model with three numbers of MFs. Fig. 11 illustrates the training error curves with different initial step sizes. It is observed that the initial values of large step sizes (0.1–1.0) strongly influence the performance. As shown in Fig. 11(b), the ANFIS model
training with initial step size of 0.6 gets converged. On the basis of foregoing discussion, the ANFIS model is finally simulated with three bell-shaped MFs and initial step size of 0.6. The passage and ANFIS surface characteristics are shown in Fig. 12(a). It suggests a resemblance and adaptation characteristic of ANFIS model with respect to noise function. The convergence of RMSE is shown in Fig. 12(b). The initial portion of the curve indicates the identification of only linear parameters while later portion for nonlinear parameters. The error cannot be minimized to zero since, the minimum error depends on the speed signal $s_i(k)$, which appears as fitting noise. Fig. 13 illustrates the estimated signals; distorted signal, speed signal and error after training.

Fig. 14 shows the MFs before and after training, in which the premise parameters corresponding to the input MFs and the consequent parameters pertaining to the output MFs are adjustable. This suggests the model adaptation. The comparative study in speed signal estimation with adaptive filters using least-mean square (LMS) algorithm is illustrated in Fig. 15. The sign-data LMS (SDL$S$) and sign-error LMS (SELS) based on MATLAB toolbox implement the sign-data and sign-error variation of LMS algorithm to determine the filter coefficients of an
adaptive filter, respectively. To analyze the sensitivity towards different values of plant parameter $T_w$, the quantitative measure in retrieval of speed signal is given in Table 3. The comparative study is made by evaluating the mean and standard deviation of speed signal (estimation) due to ANFIS, SDLS and SELS. The mean and standard deviation of speed (IS) is also tabulated. It is observed that the difference between the values of mean and standard deviation on IS and estimation signal (ES) is rather small in
case of adaptive filter noise cancellation based on ANFIS model as compared to SDLS and SELS methods. This holds true even for different values of water time constant. Also it is indicated that the RMSE values on trained data and validation data due to ANFIS model do not vary appreciably (less than 0.05). Thus ANFIS model identifies the speed dynamics more accurately than other models.

7. Conclusions

This study demonstrated the usefulness of artificial intelligence techniques to model the hydro power plant so as to identify the turbine/generator speed with random load disturbances at different values of water time constant. The prediction accuracy and the ANFIS model adaptability of ANFIS has been examined in the study. The prediction performance of NNARX and ANFIS models were compared and ANFIS model was found to learn the training data set efficiently and thus predict the unseen validation data accurately, i.e. the ANFIS model performed better than the multiple regression NN model. The study suggested a better hydro plant dynamic representation using ANFIS model.

The paper also presented an application of ANC with ANFIS based model for representation of turbine/generator speed dynamics. The passage and ANFIS surface characteristics obtained were shown to be identical. This method may prove to be effective for tracking the turbine speed dynamic changes. In hydro power plant control and operation, it is necessary to use a fast and efficient algorithm that can lead to change in turbine/generator output power to meet abrupt changes in load demand.

Appendix

Parameters of the hydro plant in study:

\[ Z_p (T_w / T_{cp}) = 6.335; \quad T_w = 2.23s; \quad T_{cp} = 0.352s; \quad T_{st} = 9.15s; \quad C_{surge} = 140s; \quad f_{runne} = 0.0475p.u.; \quad f_{penstock} = 0.089p.u.; \quad A_{gain} = 1.67; \quad U_{load} = 0.13p.u.; \quad D_{turbine} = 2.0; \quad f_0 = 0; \quad T_{ms} = 7.0s. \]

References


