Multiple-Model Adaptive Control of Hydro Turbine Generator with Fuzzy TS Models

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Abstract: - In this paper, adaptive control for hydro turbine generator is addressed. Fuzzy Takagi-Sugeno models are trained to model the turbine dynamic under various load conditions. Algorithm for estimation of the load condition is presented. On the base of the probabilities for each model from the model set “soft” adaptation is performed. The control is computed as a weighted sum from individual controllers, designed for local load conditions. An experiment is carried out that illustrates the functionality of the proposed method.

Key-Words: - Multiple models, Fuzzy Takagi-Sugeno models, Adaptive control, Hydro Turbine Generator

1 Introduction
The governors of the hydraulic turbine generating systems play an important role in the control of prime-movers of electric power system. That’s why many research papers consider the effects of governor parameter settings on the overall system performance, mainly stability and transient behavior after load disturbances. In the tasks of frequency and power control there are relatively permanent disturbances, which are result of the resistance moment variance on the turbine shaft. This resistance moment variance takes place in speeding up to the sub-synchronous speed, operation in parallel with the electric power system (EPS) as well in local network operation. The main task of the turbine governing system is to provide the stability and performance of the turbine speed and power control under a wide range of load conditions. With the advance in governor technology, the analysis of the performance of existing governors and the optimal design of hydro-turbine governors have become an important practical task. Thorn and Hill [1] utilized the state-space representation and eigenvalue analysis to analyze the controller parameters on the behavior of a single hydro unit connected to a large power system. A very comprehensive investigation of the effects of controller parameters on the overall system performance was given by Phi et al [2]. To increase the reliability and flexibility, the digital controllers have been proposed to replace the existing analog ones. Improved control algorithms have been examined, such as adaptive control and intelligent control. One of the main difficulties in the hydraulic turbine governor design is connected with the nonlinear characteristics of the hydraulic turbine that vary significantly with the unpredictable load of the unit. Such nonlinearities make the governor design a non-trivial task because governors designed for one operating condition may not work well under other conditions. This fact leads to the adaptive control algorithms [3]. However, in practice, the most governor design is based on the linearized turbine model at one load condition. The resulting controller is then de-tuned so that it can provide good performance for the worst operating conditions [1, 2]. Jiang [4] considers the analysis and design of a hydraulic turbine governor using optimal robust control theory. The advantage of this approach is that the designed governor will guarantee the stability and performance of the speed control for the entire turbine operating range. The performance of the proposed robust turbine controller is shown to be better to that of the conventional PID controller during large load disturbances.

2 Turbine Dynamics Description
The investigations have been carried out by simulations with bank of PI control algorithms in MATLAB/Simulink environment with a nonlinear plant – hydro turbine generator, described in [5,6,7]. The dynamic behavior of a hydroelectric power system is considered. It consists of a pipe that transports water from reservoir with water level $h$ to an impulse turbine type Pelton. Between the outlet of the pipe and the turbine there is a control device (nozzle) that sets the cross section $A$ of the water flowing into the turbine. The input variable is a function of nozzle aperture variation while the turbine speed is the output.

The model of the system can be developed by deriving the model of the water column, the control device model and the turbine shaft motion model. The
complete model can be obtained by connecting the three component models.

### 2.1 Turbine shaft motion mathematical model

The turbine shaft motion equation is

\[ J_t \dot{\omega}_t = M_t - M_f, \]

where \( J_t \) is the moment of inertia of the turbine shaft, \( \dot{\omega}_t \) is the turbine shaft speed and \( M_t \) is the load torque which will typically be the driving torque for an electrical generator. All variables are presented in “per units” i.e. scaled by their rated values.

The driving torque \( M_t \) depends on speed \( \dot{\omega} \) and volumetric flow \( q \)

\[ \frac{M_t}{M_f} = \left( \frac{\omega_{\text{max}}}{\omega_t} - \frac{\omega_t}{\omega_t} \right) q, \]

where \( \omega_{\text{max}} = 2 \) for Pelton turbines. Note that this will lead to a run away speed of twice nominal and a standstill torque twice the torque at nominal speed.

A small braking torque during the initial speeding up to the sub synchronous speed is due to the air and bearing friction. It is assumed proportional to speed:

\[ \frac{M_f}{M_f} = a_f \left( \frac{\omega}{\omega_t} \right). \]

As typical value is used \( a_f = 0.01 \).

Thus

\[ M_t - M_f = J_t \frac{d\dot{\omega}_t}{dt}, \]

\[ \frac{M_t}{M_f} - \frac{M_f}{M_f} = T_w \frac{d(\dot{\omega}_t/\omega_t)}{dt}, \]

where

\[ T_w = \frac{J_t}{M_f}. \]

Using equations (1), (2) and (3) it can be obtained

\[ \frac{\frac{M_t}{M_f} - \frac{M_f}{M_f}}{\frac{M_t}{M_f} - \frac{M_f}{M_f}} = \left( \frac{\omega_{\text{max}}}{\omega_t} - \frac{\omega_t}{\omega_t} \right) q + a_f \left( \frac{\omega}{\omega_t} \right). \]

A typical value is \( T_w = 3 \) s.

### 2.2 Pipe dynamics mathematical model

The pipe is of length \( L \), cross section \( A_p \) and has inlet at the elevation \( h \) where inlet pressure is zero. The outlet of the pipe has pressure \( p_p \) and volumetric flow \( q \) (water velocity \( v_p = q/A_p \)). The pipe can be regarded as a system with pressure and volumetric flow as output and input variables respectively. The inlet pressure is supposed to be the constant ambient pressure \( p_a = 0 \).

Wherefore, the flow \( q \) at the outlet of the pipe will depend on the outlet pressure \( p_p \). The linearized pipe dynamics is given is given by the transfer function

\[ H_{pq}(p) = \frac{\Delta p_p(p)}{\Delta q(p)}, \]

where \( \Delta q = q - q_0 \) and \( \Delta p_p = p_p - p_{p0} \) are the deviation from a constant solution \((q_0, p_{p0})\). Note that the negative pressure change \(-\Delta p_p\) is used in the definition of the transfer function to ensure that \( H_{pq}(p) \) has positive gain.

Assume that the water is incompressible with density \( \rho \). The equation of the water motion in the pipe is

\[ L \rho q = mgh + A_p (p_0 - p_p), \]

where \( mgh \) is the constant gravity force in the direction that acts on the water in pipe, \( p_0 \) is constant ambient pressure, and \( p_p \) is the pressure at the end of the pipe.

The water column transfer function is

\[ H_{pq}(p) = -\frac{\Delta p_p}{\Delta q} \frac{\rho}{A_p}. \]
The turbine control device transfer function is

\[ H_{qA}(p) = \frac{\Delta q(p)}{\Delta A(p)}, \]

where \( A \) is the input variable and \( q \) is the output variable. This transfer function can be obtained after rearranging of equation (13) assumed that \( \Delta p_q(p) = -H_{pq}(p)\Delta q(p) \) in accordance with (10)

\[
\left( \frac{\rho q_0 \alpha}{A_0} + H_{pq} \right) \Delta q = \frac{\rho q_0^2}{A_0} \Delta A.
\]

Therefore the transfer function from the control input \( A \) to the flow \( q \) is

\[ H_{qA}(p) = \frac{\Delta q}{\Delta A} = \frac{q_0}{\alpha A_0} \cdot \frac{1}{1 + \beta \frac{T_w}{2} p}, \]

where

\[ \alpha = \frac{2 L A_0^2 q_{\text{max}}}{\alpha q_0^2 A_0}, \beta = \frac{q_0}{q_{\text{max}}}. \]

Typical values are \( T_w = 1 \text{s}, \beta = 0.01 \) (during the initial speeding up to the sub synchronous speed). This leads to a first order lag with unity gain and a very short time constant compared with the rotor run speed time constant \( T_m \). Figure 1 visualizes the model for the subsystems presented above.

3.1 Multiple Models

Hydro turbine generator can be subjected to abrupt as well as gradual changes of the load. One way of describing this nonlinear systems is by modelling it as a hybrid dynamic system, whose state may jump as well as vary continuously. These jumps between the different modes are used to model random abrupt changes in the generators demand, such as switching on or off other generators from the electrical grid. The dynamics between the jumps is used to model the system when only individual consumers are switching on or off their household appliances.

The hydro turbine generator is system with two inputs and two outputs. We are going to control only one of the outputs - the turbine speed. One of the inputs of the turbine is opening of the nozzle, which in this paper is control variable. The other one is the load of the turbine. The load is determined by the electricity demands and it is not possible to be controlled. Thus the second input has characteristics of a disturbance. In order to be operational (connected to the electrical grid) the load of the turbine should be between 25% and 100%, which is full power. In accordance to the multiple model (MM) approach \([9,10,11,12,13]\) it is proposed a set of four models to approximate the hybrid system. The load models are, 25%, 50%, 75% and 100%

\[ M_i: y_i(k) = f_i(y(k-1), y(k-2), u(k), u(k-1)), \quad i = 1,\ldots, 4. \]

Each of the equations corresponds to a particular working regime of the system. Collectively these models are referred to as the model set \( M \).

3.2 Fuzzy TS-Models

Takagi-Sugeno (TS) fuzzy models are suitable to model a large class of nonlinear systems, including the hydro turbine generator \([15,16]\). A bank of fuzzy TS models is trained. Each of them represents a particular mode from the model set \( M \). In order to obtain a better model, a priori information for the system can be used and the models' structure can be obtained. When this technique is used, the complexity of the model is the same as the system. By using black-box techniques, lower-order fuzzy TS models can be obtained.

In order to model its dynamics second order model have been chosen. It is built on the base of two previous outputs and current and previous input. For each of the models three rules are trained.

The SISO models are of the input-output NARX type:

\[ y_i(k) = \mathbb{R}_i\left( \xi(k) \right), \quad i = 1, 2, 3, \]

with regression vector

\[ \xi(k) = [y(k-1) \ y(k-2) \ u(k) \ u(k-1)]. \]
\( R_i \) are rule-based fuzzy models of the Takagi-Sugeno type [15,16]:

\[
y(k) = \sum_{i=1}^{4} \gamma_i(k) y_i(k)
\]

(18)

In order to obtain input-output data sequences for identification for the TS-models simulation in Simulink is carried out. The block-diagram shown on Fig.1 is used, but the load condition for each model is preset. The input signal is a low-pass filtered normally distributed white noise to which white noise with a small amplitude is added. The low-frequency component signal drives the nonlinear system through the entire operating range, while the high-frequency component takes care for persistent local excitation. One thousand data points are recorded for each model. The training algorithm is c-mean clustering technique (uses the Gustafson-Kessel algorithm) [16,17]. Eight hundred points are used for the training procedure and the rest two hundred are used for model validation.

Two performance indexes are used to assess the quality of the models. They are (i) variance accounted for (VAF) and (ii) root mean square error (RMS). The VAF of two equal signals is 100% and RMS is 0. If the signals differ, VAF is lower and RMS increases. For more details see [16,17]. For the obtained models the performance indexes are presented on Table 1.

It can be seen that the results from the training are satisfactory.

Table 1. Variance accounted for (VAF) and root mean square error (RMS)

<table>
<thead>
<tr>
<th>Model (Load)</th>
<th>Training data</th>
<th>Validation data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>VAF</td>
<td>RMS</td>
</tr>
<tr>
<td>100 %</td>
<td>99.9890</td>
<td>0.0010</td>
</tr>
<tr>
<td>75 %</td>
<td>99.9937</td>
<td>8.4087e-4</td>
</tr>
<tr>
<td>50 %</td>
<td>99.9968</td>
<td>6.4086e-4</td>
</tr>
<tr>
<td>25 %</td>
<td>99.9991</td>
<td>3.6934e-4</td>
</tr>
</tbody>
</table>

3.3 Adaptive Control

Usually, control of the multiple model systems (such as (16)) is done by choosing one model from the model set \( M \) (hypothesis testing) and then control action is applied based on the selected model as if it were the “true” one. The main drawback of such approach is that it only allows a hard decision, i.e., only one model can be chosen at a given moment of time. This method does not give a good representation of partial turbine loads and hence the control performance can be poor in such case. The model set could be extended by adding partial loads modes to it. However this is not a solution, because when the models are too close to each other, problems with the statistical testing occur. Furthermore, at the moment when the control system switches from one model to another (in case of a gradual change of the load) frequent jumps of the control signal may occur. Or even worse: in the case of a load condition which is between two models the switching between the models (jumps in the control signal) may occur very frequently.

One way to solve this is by an extension of the method based on linear differential inclusions. Considering the model set \( M \), the linear differential inclusion is defined as a set of all systems that are a convex combination of the models in \( M \) [9,10,11,12,13]:

\[
M : y(k) = \sum_{i=1}^{4} \mu_i(k) y_i(k),
\]

(20)

with

\[
\sum_{i=1}^{4} \mu_i(k) = 1.
\]

(21)

where \( \mu \) is the vector containing the probabilities for each of the modes. Below this vector is called the mode probability vector. The probabilities in \( \mu \) provides the certainty that this model is the true one. Probability 1 means the load condition of the system is exactly the same as modelled for this particular model. Probability close to 0 means that the load condition in the system is very different then the modelled ones. For the adaptation purpose, the mode probabilities must be calculated for each time instant.

The proposed controllers in this paper are from PI type. They have been designed on the base of LQR technique. A bank of such controllers have been created, in such way that there is a separate controller for each TS fuzzy model (in \( M \)). In the paper it is proposed that the final control signal to be weighted sum from the control signals, obtained from the individual controllers. For the weights the mode probability vector has been used. The input to the turbine is the opening of the nozzle.

\[
o(k) = \sum_{i=1}^{4} \mu_i(k) w_i(k),
\]

(22)

where the \( o \) is the input to the turbine, i.e. the opening of the nozzle and \( w_i \) are control signals computed from the individual controllers.

Then the control of the system boils down to computing the probabilities for each model from \( M \). The whole Simulink block-diagram is presented on Fig. 2.
### 3.4 Probability Estimation

The idea behind the probability vector is to make assessment of the load condition. In this paper it is proposed to be used the difference between the real outputs of the system and the predicted ones \([9,10]\). This choice is made because it is easy to construct the fuzzy TS models (the information over the plant outputs is presented). Also in the working (on-line) regime the use of outputs is more convenient (less demanding from a computational point of view) than using estimates on their base. Of course, if the error in respect to certain model is small then the load of the system is close to the modelled one. In this paper it is proposed to be used inverse of the square root of the error. The square root is assessed of the load condition. In this paper it is proposed to be used the difference between the real outputs of the system and the predicted ones \([9,10]\). This choice is made because it is easy to construct the fuzzy TS models (the information over the plant outputs is presented). Also in the working (on-line) regime the use of outputs is more convenient (less demanding from a computational point of view) than using estimates on their base. Of course, if the error in respect to certain model is small then the load of the system is close to the modelled one. In this paper it is proposed to be used inverse of the square root of the error. The square root is chosen, because sign of the error is not important.

\[
\hat{\mu}_l(k) = \frac{1}{(y-y_l)^2} \sum_{i=1}^{4} \frac{1}{(y-y_i)^2} \quad \text{for } l=1,\ldots,4.
\]

In general, the real system is subjected to noise and disturbances. To make mode probabilities insensitive to the noise or to some disturbances, special methods have been developed. For linear systems, these include Kalman filtering, diagnostic observers, parity relations, parameter estimation and symptom analysis \([14]\). In the MM framework, techniques are available for linear systems with known mathematical models for all modes \([8,9,10,12,14]\). When probabilities are evaluated only on the base of the inputs and outputs of the system, only for the current time instant, it is possible that there appear some momentary discrepancies. In presence of strong noise the error for the correct model can become equal or even bigger than the other model(s). Another problem occurs in the transitions between two operating points (for example, after applying step signal as a reference). In order to overcome this problem it is proposed to be used the moving average of the probabilities estimation. This is done at the right side of Fig.3. This slows down the probability transition process, but copes with these momentary discrepancies in the measured turbine speed.

\[
\mu(k) = 0.98\mu(k-1) + 0.02\hat{\mu}(k) \quad \text{for } l=1,\ldots,4.
\]

### 4 Simulation Results

In this section the simulation results obtained from the proposed algorithm are presented. During the first fifty seconds of the simulation the turbine is going to sub-synchronous speed. In the next fifty seconds the turbine is working without applied load. For these intervals separate zero load controller is used. This controller is in the bottom of Fig.2. Afterwards the proposed controller is engaged. Random load disturbances are simulated. The size of the load is changed every fifty seconds. The load conditions are presented on the top of Fig.4. In the middle of the figure the speed of the turbine is shown. On the bottom of the figure the computed control signal - the opening of the nozzle is presented.

![Fig. 3: Models' probability estimation](image)

![Fig. 4: Hydro turbine signals](image)
It can be seen that the nozzle is in its operational limits, so the control did not exceed its limits. From Fig. 5 it can be observed that proposed controller is holding the turbine speed in less than ten percent from the desired value despite the change in the load. This is well below the industry standards. These perfect results are only possible due to the fact that multiple controllers for different load conditions are used. Applied "soft" adaptation provides smooth transition between different controllers and also combines there outputs when the load is in between modelled regimes.

5 Conclusion
In this paper nonlinear mathematical model of hydro turbine generator has been presented. Fuzzy TS models for particular load conditions are trained, each describing the system in a particular operating regime. By model probabilities the current load condition have been estimated. "Soft" adaptation between controllers designed for local load condition is performed. Results from simulations have been presented as well.

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