A Fuzzy Logic Decision Maker and Controller for Reducing Load Frequency Oscillations in Multi-Area Power Systems

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Abstract-- This paper deals with the application of a fuzzy logic based decision maker and controller in order to damp load-frequency oscillations in multi-area power systems. A linearised dynamic model of a two area power system is derived from that of a well known single area system and combined with the proposed fuzzy controller for simulation purposes. The fuzzy logic based controller with a decision making unit is designed to replace the classical integral type controllers. The proposed approach is compared with classical ones for performance and validity.

Index Terms-- Fuzzy control, Fuzzy logic, Fuzzy sets, intelligent control, Power system dynamic stability, Load flow control.

I. INTRODUCTION

LOAD-Frequency (L-F) control is an important task in electrical power system design and operation. Since the load demand varies without any prior schedule, the power generation is expected to overcome these variations without any voltage and frequency instabilities. Therefore voltage and frequency controllers are required to maintain the generated power quality in order to supply power to the utility under constant voltage and frequency operating conditions. The frequency control is done by load-frequency controllers, which deals with the control of generator loadings depending on the frequency. Similarly, a load-frequency controller has to be used in each area of multi-area power systems. Many research has been done and different approaches has been proposed over the past decades regarding the load-frequency control of single and multi area power systems [1-12].

The main purpose of designing load-frequency controllers is to ensure the stable and reliable operation of power systems. Since the components of a power system are non linear, a linearized model around an operating point is used in the design process of L-F controllers. However, controllers based on linearized models are not capable of supporting parameter variations for stability. Therefore alternative methods such as conventional controllers using improved dynamic models or adaptive and intelligent controllers are required. Some of the proposed methods in literature deal with system stability using fixed local plant models without considering the changes on some system parameters[8-12] as some methods use decentralized control approaches [13-16] based upon field testing and tuning in order to give robustness to the controllers. Generalized approaches based on the concepts of discontinuous control, dual mode control and variable structure systems have also been proposed [17].

The multi area power systems consist of many variables affecting the system stability in different areas. Therefore the controller designed for L-F control has to overcome the negative effects of system variables. The increasing interest and development in intelligent control techniques have become a solution to the control problems in power systems [8,9,18]. Due to its ability being able to model human decision making process and represent vague and uncertain data, the fuzzy logic based controllers have become an attractive choice in solving power system control problems [8]. Fuzzy set theory is a theory about vagueness and uncertainty. This theory provides a methodology that allows modeling of the systems that are too complex or not well defined by mathematical formulation. Fuzzy logic controllers based on fuzzy set theory are used to represent the experience and knowledge of a human operator in terms of linguistic variables that are called fuzzy rules. Since an experienced human operator adjusts the system inputs to get a desired output by just looking at the system output without any knowledge on the system’s dynamics and interior parameter variations, the implementation of linguistic fuzzy rules based on the procedures done by human operators does not also require a mathematical model of the system. Therefore a fuzzy logic controller (FLC) becomes nonlinear and adaptive in nature having a robust performance under parameter variations with the ability to get desired control actions for complex, uncertain, and nonlinear systems without the requirement of their mathematical models and parameter estimation. Fuzzy logic based controllers provide a mathematical foundation for approximate reasoning, which has been proven to be very successful in a variety of applications [10]. In modern control techniques, uncertainty and vagueness have a great amount of importance to be dealt with. The use of membership functions quantified from ambiguous terms in fuzzy logic control rules has given a pulse to speed up the control of the systems with uncertainty and vagueness.
As in many different areas, the use of fuzzy logic controller has been increased rapidly in power systems, such as in load-frequency control, bus bar voltage regulation, stability, load estimation, power flow analysis, parameter estimation, protection systems, and many other fields [11-16]. Fuzzy logic applications in power systems are given in [8] with a detailed survey.

A tremendous amount of papers and books on the control of power systems can be found in literature. Many of these papers and most of the books also cover modeling of L-F controllers [8,11-16]. Although a mathematical model of the physical systems is not required in fuzzy logic controllers for real time applications, it is necessary for digital simulation in computer environment. Therefore a simulation model for L-F controller is needed here. Since the modeling of power systems for L-F controllers are well studied in literature [1-7], it is not going to be repeated here. Well known L-F models from literature is preferred to be used instead. The modeling of the proposed fuzzy logic (FL) controller is discussed and explained clearly in the paper. Results from the proposed FLC based L-F simulation model are compared with that of classical controller. As it is well known, instantaneous load changes affect the bus voltage and its frequency causing their values swing about the nominal operating points. When the magnitudes of these swings are large and natural damping takes long time, the stability of the power system may be lost resulting in damages and power outages in the system. In order to overcome the effects of swinging frequency, some precautions must be taken such as using L-F controllers. Any load change in one of the L-F control areas affect the tie line power flow causing other L-F control areas to generate the required power to damp the power and frequency oscillations. The response time of the L-F controllers is very important to have the power system to gain control with increased stability margins. Therefore the proposed L-F controller must reduce the response time as well as reducing the magnitude of the oscillations when compared to that of classical types.

The results from classical an fuzzy logic controller are compared, and since the response time of stabilizer in load frequency control is very important, a quicker an more stable solution is achieved with FL controller than the other one.

II. THE LOAD FREQUENCY CONTROL

As it is well defined in literature [1-7], changes in real power mainly affect the system frequency while the changes in reactive power have more effects on voltage. The frequency is more sensitive to real power than it is to reactive power. Therefore, the frequency oscillations due to the changes in active power demand are damped using load-frequency controllers (LFC), which are used to maintain a reasonable uniform frequency. The first step of control engineering consists of mathematical modeling. Although fuzzy logic controllers do not require mathematical models in real time applications, they are needed for simulation purposes. Different types of models such as the one called small signal model have been drawn for LFC systems [1-7].

The load on a power system is usually the sum of two separated parts: one is the independent load required by devices such as the ones in lighting and heating, and the other part that is required by motor type loads, which are sensitive to changes in frequency. The degree of sensitivity to frequency changes depends on the total combination of the speed-load characteristics of all the driven devices. The speed-load characteristic of a composite load is approximated by

\[ \Delta P_e = \Delta P_L + D \Delta \omega \]  

where \( \Delta P_L \) is the nonfrequency-sensitive load change, and \( D \Delta \omega \) is the frequency-sensitive load change. \( D \) is a constant, expressed as the percent change in load divided by percent change in frequency.

The Laplace transform of the generator model equation (the swing equation of an synchronous machine in this case), applied on a small perturbation, leads to

\[ \Delta \Omega(s) = \left[ \Delta P_m(s) - \Delta P_e(s) \right] / (2Hs) \]

A linearized small signal model of LFC is used here as shown in Fig.1 for a single area system, where \( H \) is the machine inertia in seconds and all \( \tau \)’s are time constants.

![Fig. 2. Block diagram of a single area load frequency control.](image)

The combination of (1) and (2) results in the block Rotating mass and load in Fig.1. The source of mechanical power, commonly known as the prime mover, may be either hydraulic energy or steam. The mathematical model of the turbine relates the changes in mechanical power output \( \Delta P_m \) to changes in steam valve position \( \Delta P_v \). The most simple prime mover model can be approximated with a single time constant.

When the electrical load of the generator is suddenly increased, the mechanical power input cannot provide this electrical power. At first, this extra energy will be taken from the kinetic energy stored in the rotating system. Then, this energy will moderate causing a decrement in the generator frequency. The change in speed of the shaft will affect the governor, which will adjust the turbine input valve, whereby a new steady-state will be reached. A mechanical construction, existing of the governor and a hydraulic amplifier, tends to the feedback loop with gain \( 1/R \), which can be seen in Fig. 2 where another feedback loop is considered as an integral controller to reduce the frequency oscillations. By applying this integral controller, the steady-state frequency deviation, caused by the governor speed regulation, can be reduced to zero. Later on this integral controller will be replaced by proposed fuzzy logic controller associated with a fuzzy decision unit.

A group of generators is said to be coherent if they are coupled internally, swing in unison and tend to have the same response characteristics. Such a group of generators are included in a control area that can be represented by a load.
frequency control loop. As a simplification, a two area system is considered here. The generating units are interconnected by a lossless tie line. During normal operation, a certain amount of real power is transferred over this line. The change in the power flowing in tie line is represented by \( \Delta P_{12} \), which is a function of the generated voltages in both generators and the phase angle difference, \( \Delta \delta_{12} = \delta_1 - \delta_2 \). A small deviation in the tie-line flow can be linearized as:

\[
\Delta P_{12} = \left( \frac{dP_{12}}{d\delta_{12}} \right) \Delta \delta_{12} = P_s \Delta \delta_{12}
\]

where \( P_s \) is the slope of power angle curve at the initial operating angle \( \Delta \delta_{120} \). The tie line power flow begins whenever a load increment or decrement occurs in one of the areas.

The main objectives of the LFC system should include the followings.

- keep frequency approximately at the nominal value
- maintain the tie line flow at about schedule
- each area should absorb its own load changes.

In order to reach at these goals, a controller should be added. First an integral controller similar to those in literature is added along with the frequency deviation feedbacks over frequency bias factors, \( B_1 \) and \( B_2 \), to each area as depicted in Fig. 2. On the other hand, the power flow signal in the tie line is called as the area control error (ACE) to be used by integral controller here and by fuzzy logic controller in coming section.

simulate the system first. In Fig. 2, \( R, B, D, 1/H, P_s \) and \( K_i \)'s are constant parameters defined earlier in the text, and \( \tau ' \) are time constants. The variables \( x_1 \) to \( x_9 \) are used for: \( x_1 = \Delta \delta_{101}, x_2 = \Delta \omega_{101}, x_3 = \Delta P_{1m1}, x_4 = \Delta P_{1m2}, x_5 = \Delta P_{V11}, x_6 = \Delta P_{V22}, x_7 = \text{output from controller in area 1, } x_8 = \text{output from controller in area 2, and } x_9 = \Delta P_{12} \). Steady-state matrices can easily be written from Fig. 2.

Since there are two areas, the steady-state equation can be written with two input matrices \( B_1 \) and \( B_2 \) as in (5).

**Fig. 2. Simulation diagram of a two area system.**

The small signal simulation model of two-area power system given in Fig. 2 uses classical integral controller. In order to compare the results from the proposed FL controller with a decision maker, a classical integral controller is used to
one with the variables at stand-still. If a step change occurs in
$\Delta P_L$, power demand at time $t_0$, then the coordinates move to the
one with the origin marked as $0'$.

As seen in Fig. 3, the system load changes from $P_{L0}$ to $P_{L1}$
at the instant $t_0$. Therefore a triggering signal is produced if
the condition given by (7) exists.

\[
\text{if } t < t_0 \Rightarrow P = P_{L0} \quad (6)
\]
\[
\text{if } t > t_0 \Rightarrow P = P_{L1} \quad (7)
\]

In this case the scale of axis stays equal with the data be
moved to the coordinate system with the origin $0'$. The
process explained and given by (6) and (7) shows how the
changes in load power are represented as the triggering signal
of the system.

III. FUZZY LOGIC CONTROLLER DESIGN

As explained in the introduction, the FLC performs the
same actions as a human operator by adjusting the input
variables, only looking at the system output. The controller
consists of three sections: fuzzifier, rule base and defuzzifier,
as shown in Fig. 4. The fuzzifier first converts its two input
signals, the main signal ($\Delta \omega$ in this case), and the step change
of every sample $\Delta (\Delta \omega)$, to fuzzy numbers. It should be noted
that $\Delta \omega = \Delta \omega_0 = \Delta_1$ for the area 1 and $\Delta \omega = \Delta \omega_2 = \Delta_2$ for the area 2.
The fuzzy numbers are the inputs to the rule table, which
calculates the fuzzy number of the controlled output signal by
making the right decisions. Finally this resulting number is
converted in the defuzzifier to the crisp values.

As the classical controller the FLC also has an integrating
part to be implemented. Therefore the controller has to be
designed in such a way that the resultant incremental output
$\Delta (\Delta P(k))$ is added to the previous value $\Delta (\Delta P(k-1))$ to yield the
current output $\Delta (\Delta P(k))$. It should be noted that this is nothing
but the digital implementation of an integrator, using Euler
integration.

The FL rules in the FLC are developed to yield a similar but
more effective output than an integrator gives. The difference
between a fuzzy logic controller and an integral controller is
the procedure used to calculate $\Delta (\Delta P(k))$.

A. Fuzzy Inference System.

As shown in Fig. 4, there are two inputs to the fuzzy
inference system. The first one is the change in angular
velocity, the other one is the change of it, $\Delta (\Delta \omega(k))$. As we
want the angular velocity to be constant, the change of this
velocity can be considered as a disturbance in the system, and
should be reduced to zero as soon as possible. These two
inputs are fuzzified and converted to fuzzy membership values
that are used in the rule base in order to execute the related
rules so that an output can be generated. The fuzzy rule base,
or the fuzzy decision table, is the unit mapping two crisp
inputs, the just mentioned ones, to the fuzzy output space
defined on the universe of $\Delta (\Delta P(k))$. To simplify the
following text, the iteration counter, $k$, will be omitted from
now on.

The time response of the disturbed change in angular
velocity for an impulse input can be represented by the
generalized impulse response error of a second order system.
We are interested in the impulse response for the reason that
when a uniform step in the angular velocity, $\omega$, appears, the
derivative of $\omega$ will be one, first instants, and then zero later
on. Since the intention is to design a fuzzy logic controller
with a better performance (shorter settling time, less over-
shoot) than the classical controller, the response signal of this
system is taken as a reference to construct the rule table on.
The response signal, generated by the classical load frequency
controller for an impulse input change is given in Fig. 5. The
plot is obtained by using the matrices composed in the
previous section for the classical integral controller.

The fuzzy rules represent the knowledge and abilities of a
human operator who makes necessary adjustments to operate
the system with minimum error and fast response. It is
necessary to observe the behaviours of the error signal $\Delta \omega$ and
its change $\Delta (\Delta \omega)$ on different operating regions in order to
model the actions a human operator would take. The decision
is based upon different operating cases, deciding whether the
change, $\Delta (\Delta P)$, in the controller output should be increased or
decreased according to the inputs of the fuzzifier. This
controlled output is the required change in the input of the
system.
As been told, the result shown in Fig. 5 is useful to construct the rule table. The values we read on this graphics will be used to define the first fuzzy set intervals, which will be modified to reach a better structure with improved performance.

We first try to develop an initial rule base (with only 3 fuzzy sets), which we will extend to a 5 fuzzy sets base. According to the signs of \( \Delta \omega \) and \( \Delta(\Delta \omega) \), we decide whether the sign of \( \Delta(\Delta \omega) \) has to be positive or negative. A summary of all possible situations, or so called operation regions, is given in Table I.

Table I shows that each one of \( \Delta \omega \), \( \Delta(\Delta \omega) \) and \( \Delta(\Delta \omega) \) has three different options for the signs to be assigned. They are either positive, negative or zero. With this knowledge, an initial rule decision table with nine rules can be formed like in Table II, where 'N' means negative, 'O' zero and 'P' positive. The main part without shading represents the rules as well as the signs of \( \Delta(\Delta \omega) \).

From this table on, some logical reasoning should be considered. A closer look at Table II shows that in some cases, there is a transition from negative to positive, without passing through zero. Therefore, an adjustment in the initial rule table leads to another table without this inconvenience. The influence of \( \Delta(\Delta \omega) \) must stay, and a symmetric solution has to be advised, so the modified rule table is the one that can be found as in Table III.

A next step in designing the FLC, is the extension of the nine rules table shown in Table III to a 25 rules table, as in Table IV. In this table, two extra sets are added which gives us 5 fuzzy sets for each one of the inputs. A nine rule fuzzy decision table may be sufficient for some applications. However, many applications require more rules than nine. To obtain the 25 rules table, only a logical extension has been made.

In Table IV, a slightly different meaning of the applied letters is used: 'M' means large negative, 'N' small negative, 'O' stays zero, 'P' becomes small positive and 'Q' large positive. Now with the input sets are extended to five regions, a similar extension can be made for the output values of \( \Delta(\Delta \omega) \). The result of this logical and symmetric extension is shown in Table V. This rule table is the final one that is going to be used in the FLC here.

Now a final rule table is constructed, in which the two input domains and the output domain are divided into 5 regions, which should be defined. As suggested, the initial limits of the fuzzy sets will be derived from the diagram obtained by using the classical controller. The set values can be derived immediately from Fig. 5, but a plot of \( \Delta \omega \) versus \( \Delta(\Delta \omega) \) is preferred to identify the upper and lower limits of \( \Delta \omega \) and \( \Delta(\Delta \omega) \), clearly. A visualization of the definition of these fuzzy sets can be seen on Fig. 6 where triangular fuzzy sets are used.

In this case, the scaling of the fuzzy sets representing the partitioning will be different for \( \Delta \omega \) and \( \Delta(\Delta \omega) \). As shown in Fig. 6, the interval of the latter is much smaller yielding different scaling for a proper operation of the controller.
The fuzzy sets will initially be defined in the interval 
\[-1.5 \times 10^{-4}, -1.5 \times 10^{-4}\] for \(\Delta \omega\), and 
\[-1.5 \times 10^{-6}, -1.5 \times 10^{-6}\] for \(\Delta(\Delta \omega)\)  
(9)

The combination of Table V and Fig. 6 gives a well defined 
summary of the fuzzy sets and the rules that should be applied 
on those. The next step in the design process, is the fuzzy 
reasoning as discussed below.

B. Fuzzy reasoning

The crisp universes of \(\Delta \omega\), \(\Delta(\Delta \omega)\) and \(\Delta(\Delta P)\) have been 
partitioned into five regions as M, N, O, P and Q as explained 
earlier. These five regions in all three universes are 
partitioned into five regions as M, N, O, P and Q as explained 
earlier. The next step in the design process, is the fuzzy 
reasoning as discussed below.

A visual representation of this function is given in Fig. 7 
where \(b\) is the crisp value with a membership degree of 1 in 
the corresponding fuzzy set while \(a\) and \(c\) define the lower 
and upper limits of the fuzzy set (symmetric in this paper). 
These parameters are assigned as follows in the universe of 
\(\Delta \omega\), \(b=1.5 \times 10^{4}\) for M, \(b=0.75 \times 10^{4}\) for N, \(b=0\) for O, 
\(b=0.75 \times 10^{4}\) for P, \(b=1.5 \times 10^{4}\) for Q. A similar, equal regions 
and symmetric partition is made for the universes of \(\Delta(\Delta \omega)\) 
and \(\Delta(\Delta P)\).

Besides the definition of this triangular function, it is 
required to calculate the membership degree of \(\Delta(\Delta P)\). The 
following example is given to clarify the method used to 
control the membership values in output space. When \(\Delta \omega=0.45 \times 10^{-4}\) it intercepts with the fuzzy sets N and O in the input 
universe of \(\Delta \omega\), and when \(\Delta(\Delta \omega)=0.15 \times 10^{-4}\) it intercepts with 
the fuzzy sets O and P in the input universe of \(\Delta(\Delta \omega)\) as 
shown in Fig. 8, which is a close-up of the fuzzy-sets of Fig. 
6.

The membership degrees of all triangular fuzzy functions 
can easily be found by applying (10), in which we substitute \(a\), 
\(b\) and \(c\) by the appropriate limits; \(x\) takes the value of either 
\(\Delta \omega\) or \(\Delta(\Delta \omega)\). The horizontal lines drawn through the 
intercepting points of \(\Delta \omega\) on N and O in Fig. 8 gives the 
membership values of \(\Delta \omega\) on N and O, respectively, while the 
horizontal line passing through the intercepting points of 
\(\Delta(\Delta \omega)\) and O and P gives the membership values of \(\Delta(\Delta \omega)\) on 
these fuzzy sets, respectively. These membership values of 
\(\Delta \omega\) and \(\Delta(\Delta \omega)\) on N, O, O and P are evaluated by Table V to 
yield the fuzzy membership values of the rules at the output 
space. The interpretation of Table V results in the following 
active rules.

R1: If \(\Delta \omega\) is N and \(\Delta(\Delta \omega)\) is O then \(\Delta(\Delta P)\) is N
R2: If \(\Delta \omega\) is N and \(\Delta(\Delta \omega)\) is P then \(\Delta(\Delta P)\) is O
R3: If \(\Delta \omega\) is O and \(\Delta(\Delta \omega)\) is 0 then \(\Delta(\Delta P)\) is O
R4: If \(\Delta \omega\) is O and \(\Delta(\Delta \omega)\) is P then \(\Delta(\Delta P)\) is P

Now the application of the min-operator results in the 
following membership values from each active rule to be used 
in the output space \(\Delta(\Delta P)\). Using the same reference notations 
for corresponding rules, the results of this min-operation are 
obtained as;

\[
\begin{align*}
\mu_{R1}(\Delta(\Delta P)) &= \min(\mu_N(\Delta \omega), \mu_O(\Delta(\Delta \omega))) = \min(0.63, 0.67) = 0.63 \\
\mu_{R2}(\Delta(\Delta P)) &= \min(\mu_N(\Delta \omega), \mu_P(\Delta(\Delta \omega))) = \min(0.63, 0.33) = 0.33 \\
\mu_{R3}(\Delta(\Delta P)) &= \min(\mu_O(\Delta \omega), \mu_O(\Delta(\Delta \omega))) = \min(0.40, 0.67) = 0.40 \\
\mu_{R4}(\Delta(\Delta P)) &= \min(\mu_O(\Delta \omega), \mu_P(\Delta(\Delta \omega))) = \min(0.40, 0.33) = 0.33 
\end{align*}
\]

These resultant membership values of the active rules 
determine the weights of the fuzzy sets in the universe of 
\(\Delta(\Delta P)\). The average of these membership values, 
multiplicated with the crisp value corresponding with the 
respective fuzzy set, is used to obtain final crisp output as 
\(\Delta(\Delta P)(k)\). This final process is called defuzzification of the 
fuzzy output. Several defuzzification methods have been 
applied in literature. However, the method, called 'the center
In equation (10), \(\Delta P\), the method can be implemented as follows:

\[
\Delta(P(k))_O = \frac{\sum_{i=1}^{4} \mu_Ri(\Delta P)}{\sum_{i=1}^{4} \mu_Ri(\Delta P)}
\]

With the data of the example, this makes:

\[
\Delta(P(k))_O = (0.63)(-0.5)+(0.33)(0)+(0.4)(0)+(0.33)(0.5)
\]

\[
\Delta(P(k))_O = 0.63 + 0.33 + 0.4 + 0.33
\]

\[
\Delta(P(k))_O = 1.69 = 0.08876
\]

In equation (10), \(\Delta(\Delta P)\), is the crisp value corresponding to the maximum membership degree of the fuzzy set that is an output from the rule decision table.

IV. THE L-F CONTROL USING FUZZY LOGIC

The state-space matrices for the classical system with integral controller are composed earlier in the text. The state-space matrices of the two-area power system for the fuzzy integral controller are composed earlier in the text. The state-space matrices for the classical system with replacement of integral controller by FLC in each control area, the order of the system is reduced from 9 to 7 as in (12) and (13). Fig. 9 contains another block called decision making block. This block can be considered as a central information processing unit (CIPU), which collects speed deviation data from all controlled areas of the power system, and process a decision making algorithm to generate additional knowledge for the FLC’s. The meaning of the decision making block will be explained in next section. The system without CIPU will be considered first.

![Fig. 9 Fuzzy Logic basic block diagram.](image)

\[
B1 = \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
0
\end{bmatrix} \quad B2 = \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
0
\end{bmatrix} \quad B3 = \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
0
\end{bmatrix} \quad B4 = \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
0
\end{bmatrix}
\]

So the steady state equations become:

\[
\dot{x} = Ax + B1u1 + B2u2 + B3u3 + B4u4
\]

V. THE L-F CONTROL WITH DECISION MAKER

Although the initial set of fuzzy logic rules did not give a desired performance to reduce the oscillations better in a shorter time than the classical integral controller does, effective results are obtained using the final rule table given by Table V. By making some adjustments in the intervals, found by using trial-and-error, results better and similar to those from the classical integral controller are achieved, as will be discussed in section with subtitle results. However the results are still not as good as they are expected to be. Therefore some additional process is required to support the basic fuzzy logic controllers.

Since the fuzzy logic controller has the intention to operate in the same way like a human being would do, and since humans are always capable to think a bit further when the right results are not obtained, the fuzzy logic controller will also be made a bit 'cleverer'. Therefore, a 'decision making block' is inserted, as shown in Fig. 9.

If a load change occurs in plant 1, its angular velocity will slow down. Plant 2 follows this movement, and will also slow down, but some seconds later. More mechanical power will be delivered to plant 1, and some seconds later to plant 2. Due to this retardation, too much extra mechanical power will be delivered to both plants that cause the large oscillations without any damping of at least one of the signals. At this
point, a decision making unit is introduced. This unit compares the angular velocity of plant 1 and 2, and sends an extra control signal to the fuzzy logic controllers of both plant 1 and plant 2. If the velocity is bigger in plant 1, the extra control signal sent to plant 1 will be 1 or close to one and the signal to plant 2 will be smaller, commonly between 0 and 0.5. This signal is the factor used to multiply the values in the universe of $\Delta x$ with, what will result in a quicker change of extra mechanical power for plant 1 and only a small change in mechanical power for plant 2 if the disturbance of plant 1 is biggest at that moment.

The two extra control signals are also influenced by the value of the angular velocities ($x_1$ and $x_2$) of the plants in such a way that if both $\Delta \omega$'s are little, both factors will be very small too.

VI. RESULTS

Both of the systems will be simulated using the following parameter values:

\[
\begin{align*}
D_1 &= 0.6, D_2 = 0.9, H_1 = 5, H_2 = 4, R_1 = 0.05, R_2 = 0.0625, \\
\tau_{\delta 1} &= 0.2, \tau_{\delta 2} = 0.3, \tau_{\theta 1} = 0.5, \tau_{\theta 2} = 0.6, P_1 = 2, \\
K_H &= K_{I 2} = 0.3, B_1 = 20.6, B_2 = 16.9, \Delta P_{L1} = 0.2, \Delta P_{L2} = 0
\end{align*}
\]

First the system is simulated using only the integral controller. The resultant graph of the integrator controlled system can be seen in Fig. 10. The oscillations in both areas are damped and reduced to zero by the integral controller. Then the system is simulated when only the fuzzy logic controller is in present. The results obtained by the fuzzy logic controlled system are shown in Fig. 11. The system is stable, and the frequency deviations tend to go towards a zero steady state error. However, the frequency deviation from the Area 2 has a longer time than it is for Area 1. The response for Area 1 is much faster than the response obtained with integral controller with a reduced oscillation magnitude. However, the same comment cannot be made for the response coming from the Area 2, in which there is a longer settling time with a faster damping. More improvement needed to be make both responses from areas 1 and 2 to have shorter settling times as well fast damping effects.

After the addition of the proposed decision making unit, an improvement has been made to the fuzzy logic controllers in both areas. Results using the decision making unit are given in Fig. 12. The decision making block with the ability of operating as a central information processing unit results in a faster, stable and zero steady state error for both areas. The signal can be manipulated in such a way that the settling time becomes shorter while a considerable reduction obtained in overshoot with a faster damping.

Both plots in Fig. 12 have a zero steady state error, just like the integrator and FL controlled responses. However, a visible improvement in settling time, damping speed and steady state error can be observed by comparing the figures.

VII. CONCLUSIONS

Load frequency controller based on fuzzy logic theory, with addition of the decision making block, has been designed and compared with the classical one, commonly known as the governor + integrator system. The results from both proposed FL based controller and classical methods were obtained for a
step reference input for comparison. The output of the load change was controlled with less overshoot or shorter settling time using the fuzzy logic based controller with decision making unit. And since many expensive electrical devices are very sensitive to high frequency fluctuations and the FLC restricts the overshoot, it is highly recommended to apply the fuzzy logic controller instead of the classical one.

The classical integrator increases the order of the system's dynamic model causing additional delaying terms, which are not in present when FLC is used. However, FLC introduces a time delay as well due to the time required by the algorithm used to process the operations done by fuzzy inference system. Therefore a care must be given to the algorithm processing FLC actions. The delay caused by the algorithm is a burden in fuzzy logic controllers that has to be reduced. Using an algorithm that processes only the active rules for each sampling instant, rather than all twenty five rules may be a solution to this burden. The use of appropriate fuzzy sets may also be a solution. However, an additional unit, called decision maker, is used instead. With the decision unit, the control signals are generated separately for each controlled area depending on the effect of the load increments on the frequency changes in each area. Therefore the required mechanical power is generated in the amount needed in each area.

The fuzzy logic based controller gives a performance that is quicker and has less overshoot. It operates on the basis of a human operator's thoughts and executes the rules to adjust the system input by just measuring the output and making some extra logic decisions. The rules are generated for a large decision space, so that the aging and some other operating effects on the system parameters do not affect the rules and the controlled system. Since FL based controllers do not affect the order of the system dynamics, the only delay occurs due to the algorithm that is used to process and execute the active rules. The simplification made by fuzzy logic controller is a cost reduction advantage that is still one of the most important industrial decision making elements.

VIII. REFERENCES


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