The Online Estimate of System Parameters For Adaptive Tuning on Automatic Generation Control

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Abstract—Making balance between the generation and demand is the operating principle of the load frequency control (LFC). Several studies in LFC have led to the trend of applying the adaptive approach to the implementation on automatic generation control (AGC). However, the adaptive controller with self-tuning technique requires online acquisition of system parameters that was not clearly stated in the related literatures. This paper proposes the online Recursive Least Square (RLS) estimation on system’s parameters for an isolated power system. The estimated parameters not only could be used as a reference model for the design of the nominal gains in gain scheduling technique, but also could be applied to the online tuning of the controller gains under the time-varying condition. Simulation results show that the RLS based estimate with an adaptive controller could enhance the performance of the LFC.

Index Terms—Load frequency control, Automatic generation control, Adaptive control, Gain scheduling.

I. INTRODUCTION

Whenever the system encounters a noticeable disturbance either from the load or generation loss, the frequency will start to deviate from the nominal value. If the frequency excursion is not properly controlled, the load shedding and cascading unit trips would be detrimental to system’s reliability. How to control the frequency within the safe range in order to ensure system’s security and power quality is the philosophy of the load frequency control.

After speed-governors reacting to arrest the runaway frequency from a disturbance, the function of AGC is to automatically adjust units’ set-points for power compensation so that frequency could return to nominal value. In practice, most utilities still use conventional PI controller in the AGC structure. Although such a control technique is simple to implement, the performance is not satisfactory. Due to the nonlinearities and time-varying behaviors inherent in the power system, the performance of AGC depends on the system response at the moment of action. Some studies have shown that should AGC not properly respond to the operating states, extraneous or inadequate reactions could degrade power quality or lead to additional cost [1]–[3]. As a result, strategies attempting to employ system’s operating states for control reference have been developed to achieve better dynamic performance. Among different techniques that realize model reference control, the adaptive PI controller with self-tuning gain technique is appealing to implement or upgrade for the current PI structure. To implement such an adaptive controller, the online estimation of system parameters for the adaptive controller is essential [4]–[6].

This paper first reviews the LFC loops and points out some important system parameters that dominate LFC dynamics. Following that, we propose a RLS algorithm to estimate system parameters online. Results from simulation and field data testing confirm the traceability of the proposed algorithm in the time-varying condition. An adaptive fuzzy gain scheduling controller is also demonstrated to offer better performance in the nonlinear and time varying operating conditions.

II. THE LOAD FREQUENCY CONTROL LOOP

Fig. 1 depicts the primary and secondary control loops of LFC for an isolated power system. Whenever there is unbalance between generation and demand, the deviated frequency would first invoke primary compensation by effective speed-droop \( R_{eq} \) of governors. The amount of governor response is determined by the following relation

\[
\Delta P_1 = \frac{1}{R_{eq}} \Delta F
\]  

(1)

With governor and load damping responses, the frequency is deviated at \( \Delta F \). To eliminate \( \Delta F \), the secondary control attempts to adjust generation in a higher but slower level, whose functions are to take over system’s primary support, to compensate its load change, and to maintain frequency at scheduled value. For a load disturbance \( \Delta P_L \) occurs in the isolated power system, the load-frequency relationship could...
be depicted in the form [7]

$$\Delta F = -\frac{\Delta P_L}{R_{eq}} + D$$

(2)

where $D$ is referred as load damping. The composite term, ($\frac{1}{R_{eq}} + D$), is also referred to the frequency response characteristic, $\beta$ [1], [2].

To compensate $\Delta P_L$, the amount of secondary control adjustment should be

$$\Delta P_2 = -\beta \cdot \Delta F$$

(3)

Since system’s $\beta$ is not measurable but is approximated, most utilities use frequency bias $-10B$ to offset $\beta$ for indicating power imbalance, which is depicted in the form

$$SCE = (-10B) \cdot \Delta F$$

(4)

where $SCE$ is regarded as area’s System Control Error. The engineering unit of $B$ is in MW/0.1Hz, numerically negative.

$SCE$ not only indicates area’s generating deficiency within its territory, but is employed to calculate the generation adjustment in the secondary control. If an integral controller is adopted in the AGC structure, the regulation amount would be

$$P_I = -K_I \int SCE \, dt$$

(5)

where $K_I$ is the integral gain. Although integral controller could eliminate steady state error of frequency, the frequency restoring time and oscillation may not be satisfactory. Therefore, proportional and derivative controllers that could expedite the restoring process and increase the damping effect are supplemented to the integral controller. The regulation amount from AGC would then be reformed as

$$P_{REG} = -K_P SCE - K_I \int SCE \, dt - K_D S\dot{C}\dot{E}$$

(6)

Since the functions of PD controllers are to improve the transient states, the PD gains are generally set according to $\Delta F$ and $\Delta \dot{F}$. Fig. 2 shows the application of PD gain scheduling technique in a utility’s AGC system. However, the setting of integral gain $K_I$ is not that straightforward. Our investigations on the integral controller have shown that the generation response, system $\beta$, and system’s rotating inertia are three major factors that influence the performance of the integral control. The rationale for this conclusion is illustrated in the following sections.

### III. Identify a Model for Generation Response

From the system modelling point of view, system’s generation response could be represented by a lumped generation model. What type of the generation model that could closely emulate the generation dynamics in the real system, and be feasible for online estimation for model parameters are the main subjects to be discussed in this section.

Generally, the types of generating units for frequency regulation may differ from one to the other. For example, Hydro generators can respond within 10 seconds and can ramp from 0 to 100% within one minute [7], [8]. Therefore, they are the prior choice compared to the other types of units because of their fast response and low operating cost. However, the lack of hydrological support in some situations may hinder the use of hydro plants. In such a case, another choice may pass on to the combustion or combined-cycle turbines. These turbines can respond within 10 seconds and can ramp up from 10 to 21 MW/min. Although some coal-fired power plants are employed in frequency control in some utilities, the inherent delays and slow reactions may pose problems to the control efficiency [9].

The power curves in Fig. 3 demonstrate the different types of unit outputs subject to a step change in load reference.

![Fig. 3. Various types of unit outputs subject to a step change in load reference](image)

The power curves in Fig. 3 demonstrate the different types of unit outputs subject to a step change in load reference. The results are based on the simulation from the unit models in [10], [11]. This figure shows that the fast response units are more capable of dealing with load disturbance. Based on Fig. 3, units’ ramp rates could be depicted in Fig. 4. The line denoted as "slope total" represents sum of the ramp rates of the four different units. The slope_total line shows that system’s ramp rate is close to that of the fast regulating unit. It also
implies that system’s regulating dynamics is dominated by the fast response plants.

Fig. 5 shows that system’s step generation response could be affected by unit allocation. The solid, dash, and dot curves denote the different unit allocation under ratio (fast to slow units) at 0.8/0.2, 0.5/0.5, and 0.2/0.8, respectively. The curves imply that system’s generation dynamics could change from different unit allocation. In this test, we proceeded the transfer functions subject to the referred allocation ratios above. The transfer functions are shown in (7), (8), and (9) for allocation ratios at 0.8/0.2, 0.5/0.5, and 0.2/0.8, respectively.

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.8} = \frac{80.65(s + 69.3)(s + 12.4)(s + 3.2)(s + 0.1)}{(s + 50)(s + 25)(s + 12.3)(s + 5)(s + 3.2)(s + 0.1)} \quad (7)
\]

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.5} = \frac{55.38(s + 68)(s + 8.6)(s + 3.7)(s + 0.1)}{(s + 4)^2(s + 50)(s + 25)(s + 8.1)(s + 0.1)} \quad (8)
\]

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.2} = \frac{30.09(s + 64.5)(s + 10)(s + 3)(s + 0.14)}{(s + 50)(s + 25)(s + 5.9)(s + 4.2)(s + 3.1)(s + 0.1)} \quad (9)
\]

In practice, it is difficult to identify a higher order model in realtime. Therefore, a technique of model order reduction in [14] is adopted to eliminate the unnecessary states in (7). It follows that the equation can be reduced to

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.8} = \frac{2.8715}{(s + 2.776)} \quad (10)
\]

(10) could be further approximated as follows

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.8} = \frac{1}{0.348s + 1} \quad (11)
\]

which could be represented in the form

\[
\left\{ \frac{\Delta P_{\text{out}}}{\Delta P_{\text{in}}} \right\}_{\text{fast} = 0.8} = \frac{1}{T_{P}s + 1} \quad (12)
\]

The generation response from a sixth order model versus the response from a reduced first order model is also shown in Fig. 5. The figure revealed that with higher allocation ratio on fast units, the response from a first order model is more close to that from the sixth order model. It implies that the generation model could be approximated by a first order equation, providing that more fast units are allocated for regulation. Under the current practice on LFC, fast units are commonly employed to facilitate the regulation response. As a result, we can conclude that a first order equation with appropriate time constant \(T_P\) could represent the generation response of the system.

**IV. IDENTIFY IMPORTANT SYSTEM PARAMETERS FOR THE LOAD-FREQUENCY RELATION**

The load-generation balance is mainly reflected by the system frequency. Whenever the power disturbance occurs in the system, frequency will drift at some excursion rate and stop at some range. From (2), we can see that the rate of frequency change is affected by the lumped rotating inertia of the online units, \(M\). However, the extent of frequency deviation is determined by system’s \(\beta\).

Some literatures in LFC addressed the importance of system’s \(\beta\) on frequency dynamics [1], [7], [15], [16], [3] and [17] proposed the variable frequency bias setting corresponding to \(\beta\) for better AGC performance. In [18], system inertia, \(M\), was utilized to calculate generation deficiency for the operation of under-frequency load shedding. Therefore, it stands to the reason that \(\beta\) and \(M\) are the other two important system parameters for LFC.
V. **Online estimation of** $T_P$, $\beta$, $M$ **using RLS algorithm**

From section III and IV, we conclude that these three important system parameters ($T_P$, $\beta$, $M$) have major effects on the response of LFC. Our next step is to estimate these parameters in realtime so that integral gain $K_I$ in AGC could be properly tuned accordingly for the dynamic system.

A. **Online estimation of generation time constant** $T_P$

Based on section III, the input and output relations could be approximated by

$$P_{in} \times \left( \frac{1}{T_P s + 1} \right) = P_{out}$$  \hspace{1cm} (13)

where $P_{in}$ is unit’s MW input commands, $P_{out}$ is unit’s actual MW output. Relocating the denominator and taking the inverse Laplace transform, (15) becomes

$$P_{in} = P_{out}' \times T_P + P_{out}$$  \hspace{1cm} (14)

where $P_{in}$ and $P_{out}$ could be collected from RTU-SCADA system. With the available $P_{in}$ and $P_{out}$, $P_{out}'$ is calculated by Newton type algorithm [18]. $T_P$ is then easily obtained consequently.

B. **Online estimation of system’s inertia constant** $M$ and $\beta$

According to Fig. 1, the electromechanical power balance equation of an isolated power system is

$$(P_{out} - P_L) \times \frac{1}{Ms + D} = \Delta F$$  \hspace{1cm} (15)

where $P_{out}$ is total MW generation, $M$ is system’s inertia constant in second, $\Delta F$ is frequency deviation in Hz, $D$ is load damping in MW/Hz, and $P_L$ is system MW load. Relocating the denominator term in (15) and taking the inverse Laplace transform, (15) becomes

$$P_{out} = M \times \Delta \dot{F} + D \times \Delta F + P_L$$  \hspace{1cm} (16)

It is noted that $P_{out}$ and $\Delta F$ are commonly available from area’s SCADA system. $\Delta \dot{F}$ could also be obtained by Newton type algorithm. $P_L$, $M$ and $D$ could be estimated online by RLS algorithm [19]. Once $D$ is made available, system’s $\beta$ is calculated by adding plants’ droop responses from online monitoring of units’ response curves.

VI. **Performance of algorithm on simulation**

The RLS algorithm was first verified on a simulation environment that had been developed according to Fig. 1. The testing load data sampled from a utility was used as a forcing function to run the LFC simulation. In the test scenario, we changed unit allocation (fast to slow unit ratio) at the 44th s, and varied system’s $\beta$ and $M$ at the 86th s throughout the simulation run. The estimation results are shown in Fig.6.

The third subplot of Fig. 6 shows that $T_P$ was successfully traced when unit allocation had been changed. $T_P$ was initially estimated around 0.334 s, then changed to 0.328 s. The fourth and fifth subplots in Fig. 6 show that the traces of $\beta$ and $M$ also reflected the pre-assigned changes in the system. The second subplot of Fig. 6 shows that a sudden change of unit allocation or load may result in a larger frequency perturbation.

VII. **Performance of algorithm on field test**

The feasibility of the $T_P$ estimation by RLS algorithm can be demonstrated from its performance on actual field data sampled from a utility. A sample result from such a test is given in Fig. 7. With desired generation input (marked in dot line) and actual generation output (marked in solid line), $T_P$ was estimated in realtime, then the first order generation model was built according to (13). The output of the generation model (marked in dash line) is compared with the actual generation. The close traces between these two thick lines confirm the proposed first order model in emulating the actual generation response.
VIII. APPLY PARAMETER ESTIMATES TO FUZZY GAIN SCHEDULING TECHNIQUE

A. Schedule integral gains with nominal operating conditions

Once the system parameters are available, the integral gains in AGC could be scheduled corresponding to some nominal operating conditions. In general, the operating states of LFC in a control area could be categorized into three load conditions, on peak, semi-on peak, and off peak. Each state may result in different $T_p$, $\beta$, and $M$ in the system. As a result, three parameters for three states would constitute 27 patterns of operating gains.

The optimal integral gains for the 27 patterns are scheduled by Genetic Algorithm (GA). The fitness function is the criterion for GA to adopt superior candidates for the optimal solution. To eliminate frequency deviation, we suggest the following fitness functions for different performance criteria:

1. if the expected LFC performance is to avoid over-regulation or power oscillation, the fitness function is

$$\text{minimize } \int |\Delta F| \, dt \tag{17}$$

2. if the expected LFC performance is to speed up the AGC response in a short period of time, the fitness function is

$$\text{minimize } \text{mean}(|\Delta F|)^2 \tag{18}$$

Suppose a faster AGC response is focused for the control criterion, we chose the fitness function in item 2 for GA to proceed gain optimization. The optimized integral gains corresponding to 27 patterns are listed in Table I.

B. Derive off nominal gains by Sugeno fuzzy approach

Owing to the nonlinearities and time-varying conditions inherent in the actual system, the system parameters may not fall into the nominal patterns that are listed in Table I. In this case, a Sugeno Type Fuzzy Inference System (STFIS) was adopted to calculate the off nominal gains. Unlike Mamdani type fuzzy inference approach, STFIS does not use the complicated defuzzification process to derive the off nominal gains. As a result, STFIS is simpler to design, faster for AGC calculation. The steps for STFIS approach is described as follows:

1) construct the membership functions: When $T_p$, $M$, and $\beta$ are monitored, the estimated values are fuzzified by the membership functions depicted in Fig. 8. The membership functions are to be used for fuzzification process.

2) setting the fuzzification rule: The available $T_p$, $M$, and $\beta$ are classified into three subsets (S,M,L) shown in Fig. 8. Assume $T_p$, $M$, and $\beta$ belong to subsets $a_1$, $a_2$, and $a_3$, respectively, then the gain of the $i^{th}$ rule would correspond to $K_i$. The membership values of the fuzzy variables $\mu(a_1)$, $\mu(a_2)$, and $\mu(a_3)$ are also obtained.

3) calculate controller gain: The crisp value of gain $K_i$ is computed as follows

$$K_i = \frac{\sum_{i=1}^{27} \alpha_i K_i}{\sum_{i=1}^{27} \alpha_i} \tag{19}$$

where $\alpha_i$ is the firing strength of the $i^{th}$ rule, which is calculated from the minimum of membership values associated with the $i^{th}$ rule.

IX. SIMULATION TEST ON FUZZY GAIN SCHEDULING CONTROLLER

The LFC simulation test bed was constructed to verify the effectiveness of the fuzzy gain scheduling controller when system is under off nominal and nonlinear operating conditions. Within the LFC loop, we applied 15mHz speed governor deadband to all online units. Table II shows the RMS values of $\Delta F$ associated with different types of controllers. For
comparison, the other two gains are adopted from fixed gain and nominal gain scheduling techniques. The smallest RMS value of \( \Delta F \) in Table II reveals that the STFIS type controller is superior to the other types of controllers.

X. CONCLUSION

Our investigations of the load frequency control behavior induced three system parameters \((T_p, \beta, M)\) that have major influences on the system frequency and unit response subject to the load disturbances, which in turn could also affect the performance of the automatic generation control. Since \(T_p\), \(\beta\), and \(M\) are dependent on the type of unit allocations and load-frequency characteristics, their values are time varying.

In this paper, we have presented a RLS algorithm to estimate the three parameters in realtime. The estimation algorithm only needs inputs that are commonly available in most utilities’ SCADA systems. Following the presentation are the algorithm testings on simulation, and on field data. Test results indicated that the algorithm was performing as expected.

The proposed RLS algorithm can be used in conjunction with the gain scheduling technique or a model reference control. The estimated LFC parameters could be gainfully used either in the process of offline gain scheduling or in the process of online gain tuning. The LFC simulation using the online parameter estimate with fuzzy gain scheduling technique has proven its superiority in dealing with nonlinear and time varying conditions, compared to the other testing controllers in the LFC application.

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REFERENCES


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