An On-Line AGC Compliance Evaluator

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This paper presents a method to calculate the compliance of a given operating generator acting under automatic generation control (AGC). It is a measure of how far the actual output will deviate from the desired MW output. The approach also applies the Signal Processor Toolbox from Mathworks to derive a polynomial equation representing the transfer function relating the desired input to the actual output signal. The transfer function will be used to generate expected output responses for given desired input signals. These expected output responses are compared to the actual output responses for various types of transfer functions. This approach has been tested on nine different units supplied by PJM interconnection.

KEYWORDS: Regulation, Load following, Deregulation, Automatic Generation Control, MATLAB, Ancillary Services.

1. INTRODUCTION

Not so long ago, in the controlled and regulated market, a power utility might not have been very interested in operating its system to achieve maximum profitable generation. Today as the power market expands with the introduction of a deregulated environment, a complete balanced system with high efficiency is sought to achieve a maximum profitable return. In this mode of transaction, power users or the market for bulk power electricity will have a choice in selecting the utility or company to regulate their electrical needs. This seems like a simple philosophy but the implementation requires some form of systematic approach to yield a comprehensible and feasible series of actions in the process [5]. This consists of continuous power transfer stability, improved load-forecasting capabilities, balanced and reliable power delivery, trusted auxiliary services, etc. This need is due to the fact that every single activity in power system operation requires a precise measurement and execution in order to minimize unacceptable losses in a participating company [11]. This paper addresses a specific aspect of auxiliary or ancillary service, generator regulation through automatic generation control (AGC).

Deregulation of the power market force utilities or power providers to supply a very reliable and balanced energy source as well as reasonable pricing information according to the services applied [8]. In the ancillary market, it is in the transmission system operator’s (like PJM) interests that all participating companies provide sufficient and reliable information regarding the regulating capability of participating units. Nevertheless, it has been noticed that some participating units do not perform or regulate “up to par” thereby putting more stress on the remaining units that do perform adequately. In addition, among the adequately performing regulating units, there is an incentive to measure “how good” they regulate. This would affect the participating parties’ bidding scheme as well as the ancillary market’s pricing scheme.

A measure of AGC compliance is needed to describe the performance of regulating generators. Such a measure would provide certain insights such as a definition of a threshold compliance value separating the good from bad performing generators. In addition, one can also envision the development of a model of a specific unit’s regulation based on measured data depicting its response to a time-varying set of input signals. This model or transfer function could then be used for off-line studies for the purposes of improving bidding and pricing schemes. Another use for such a function could be in operation as a real-time predictor of system regulation. Section 2 will discuss the current problem at hand and will be followed by the solution methodology in the paper in section 3. Results and conclusion are addressed in sections 4 and 5, respectively.

2. PROBLEM DESCRIPTION

In this paper, the driving factor for compliance analysis is the time-varying real-time desired generation. The units, by engaging themselves in deregulation trading activity will expose themselves to very rapid and nonlinear fluctuations in the load [12]. Thus, compliance analysis requires a comprehensive mathematical tool to account for the time varying load function. Figure 2.1 shows a plot of the actual and pre-determined (or desired) responses of the generator for a particular time interval. Pre-determined values depict the scheduled MW (desired generation) sent to the generator from the system operator. Actual response depicts the measured values of a given generator output. Later in the paper, the derivation of compliance metrics will be discussed and explained in detail. In addition, based
on the real-time response of a generator to a scheduled MW, the transfer function analysis is performed. A transfer function model can be helpful in the area of operational planning are needed. It is also useful in terms of predicting on-line regulation behavior.

In compliance analysis, the main issue is the ability of the generator to track the scheduled MW or control signal in a real-time environment. The generators tested are those that are operating freely in the open (deregulated) generation market. It is in this market where the load behaves unexpectedly that compliance analysis should depict the performance of generators under such conditions. Hence, this paper describes compliance as an error between two signals, actual generation acting under AGC commands and the scheduled MW output (function of actual MW load). To accomplish this, the mean error and correlation between the two signals serve as final measures, which will illustrate the unit’s compliance over some selected time frame.

3. PROGRAM FORMULATION

In this paper, there are four main steps involved in the analysis. The first step is where a complete data set from a unit is analyzed. This analyzed data will be smoothened through filtering (2nd step). This is soon followed by compliance analysis, which applies statistics to define the responsiveness of the generator acting under scheduled MW (3rd step). The fourth and final step entails a transfer function analysis that links the desired generation to the actual output response. Figure 3.1 shows an overall structure for the analysis.

3.1 Unit Input-Output Analysis

In this part, there are three types of operational information (that make up the input-output information) supplied by the utility in a bidding process. The first is the unit’s economic bid data set. This constitutes the unit’s total MW bidding price (dispatch rate-bid) \( \lambda_{\text{bid}}(t) \), bidding MW \( P_{\text{bid}}(t) \), and the slope \( (\Delta \lambda_{\text{bid}}/\Delta P_{\text{bid}}(t)) \) of the line passing through points \( (\lambda_{\text{bid}}(t), P_{\text{bid}}(t)) \). Table 3.1 below shows an example of operational information.

<table>
<thead>
<tr>
<th>( P_{\text{Bid}} )</th>
<th>( \lambda_{\text{Bid}} )</th>
<th>( \Delta \lambda_{\text{Bid}}/\Delta P_{\text{Bid}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>MW</td>
<td>$/MWh</td>
<td>$/(MW)^2 h</td>
</tr>
<tr>
<td>27</td>
<td>37.7</td>
<td>0.0087</td>
</tr>
<tr>
<td>54</td>
<td>40.3</td>
<td>0.09629</td>
</tr>
<tr>
<td>81</td>
<td>42.9</td>
<td>0.09629</td>
</tr>
<tr>
<td>108</td>
<td>45.4</td>
<td>0.09259</td>
</tr>
<tr>
<td>135</td>
<td>48</td>
<td>0.09629</td>
</tr>
</tbody>
</table>

The second part is the regulation bid data set and it consists wholly of the company’s assigned regulation signal, \( p_{\text{ass}}(t) \).

The last part is represented by the system parameters. Here, the actual power output, \( P_{\text{Actual}}(t) \), dispatch rate, \( \lambda_i(t) \), company’s and unit’s regulation signals, \( p_{\text{com}}(t) \) and \( p_{\text{unit}}(t) \), respectively are presented. All these three parts of operational information will be called unit data set. This unit data set is used to generate desired MW output or regulation set points, \( P_{\text{Desired}}(t) \) which varies as a function of time. The proceeding will discuss the issue of desired MW derivation in detail.

To perform this derivation, first, the bid curve ($/MWh vs. MW) for the unit is first generated. The plot based on Table 3.1 is given in Figure 3.2 below for a certain generator.
Two important points should be noted from the plot. First, $P_{\text{max}}$ and $P_{\text{min}}$ or the maximum and minimum output of the generator are within the bid curve. Mathematically, this condition is given by

$$P_{\text{Max}} \leq P_{\text{BidMax}} \quad (3.1a)$$

$$P_{\text{Min}} \geq P_{\text{BidMin}} \quad (3.1b)$$

These max and min outputs are given by:

$$P_{\text{Max}} = P_{\text{RateMax}} - \Delta P \quad (3.2a)$$

$$P_{\text{Min}} = P_{\text{RateMin}} + \Delta P \quad (3.2b)$$

$p_{\text{RateMax}}$ and $p_{\text{RateMin}}$ are rated maximum and minimum output powers of the generator. $\Delta P$ is the safety “buffer” zone provided by the system operator (e.g. PJM) which is equivalent to the assigned AGC signal, $p_{\text{Unit}}^{\text{Bid}}$.

Second, based on different slopes, $\Delta \lambda_{\text{Bid}}/\Delta P_{\text{Bid}}$ and dispatch rate-bids, $\lambda_{\text{Bid}}$, segmentation of the bid curve according to its slopes is performed. For example, as shown in Figure 3.2, suppose there are $m$ segments, we obtain desired generation given by

$$\lambda_i(t) = f(P_{\text{Desired}}(t)) \quad \text{or} \quad P_{\text{Desired}}(t) = f^{-1}(\lambda_i(t)) \quad (3.3)$$

where $P_{\text{Desired}}$ is our initial estimate of desired generation. Because of linearity, we calculate the desired generation using the equation given below.

$$P^{\prime}_{\text{Desired}}(t) = \frac{\lambda_i(t) - (\lambda_i(t) - \lambda_{\text{intercept}})}{\text{slope}(t)} \quad (3.4)$$

Where slope $(t)$ is the value of “$\Delta \lambda_{\text{Bid}}/\Delta P_{\text{Bid}}$” at the time, t. $\lambda_{\text{intercept}}$ is the intersection of the line connecting the two bidding points on each segment extended to the $\lambda$-axis. The logic that follows for the first and last segments is characterized below.

$$P^{\prime}_{\text{Desired}} \geq P_{\text{Max}} \quad \iff \quad P^{\prime}_{\text{Desired}} = P_{\text{Max}} \quad (3.5a)$$

$$P^{\prime}_{\text{Desired}} \leq P_{\text{Min}} \quad \iff \quad P^{\prime}_{\text{Desired}} = P_{\text{Min}} \quad (3.5b)$$

In addition,

$$P_{\text{Min}} \leq P^{\prime}_{\text{Desired}} \leq P_{\text{Min}} \quad \iff \quad P^{\prime}_{\text{Desired}} = P^{\prime}_{\text{Desired}} \quad (3.5c)$$

holds for equation (3.4), where $P^{\prime}_{\text{Desired}}$ is our second level estimate of desired generation.

To complete the derivation, desired generation, regulation and assigned regulation signals are applied to the equation. In the final calculation, the following mathematical expression is added to any of equations 3.5 above.

$$p_{\text{unit}}^{\text{Reg}} = p_{\text{com}}^{\text{Reg}} - p_{\text{ass}}^{\text{Reg}} \quad (3.6)$$

Where $p_{\text{com}}^{\text{Reg}}$, $p_{\text{ass}}^{\text{Reg}}$ and $p_{\text{unit}}^{\text{Reg}}$ are company regulation, company assigned regulation and unit assigned regulation set by system operators, respectively.

Thus, the third estimate and final desired generation value is

$$P_{\text{Desired}} = P^{\prime}_{\text{Desired}} + p_{\text{Reg}}^{\text{Unit}} \quad (3.7)$$

### 3.2 Averaging of Unit’s Data

The next step involves applying the moving averaging technique to the two signals, $P_{\text{Desired}}$ and $P_{\text{Actual}}$. The equation used is given below:

$$p_{\text{Ave}}^{\prime}(k) = \frac{\sum_{j=1}^{m} p_{\text{Desired}}(j)}{m} = \frac{\sum_{j=1}^{m} p_{\text{Desired}}(j)}{m} \quad (3.8)$$

where “…" can be either “desired” or “actual” and the value of $m$ determines the size of the interval used in the moving average technique. In our studies, we investigated values of $m$ ranging from 20 to 30. In terms of a sampling rate of 4 samples/min, 20 samples is equivalent to 5 minutes. After performing this process, the desired and actual values are redefined by these averaged values or $P_{\text{Ave}}^{\prime} = P_{\text{Desired}}^{\text{Ave}}$.

### 3.3 Compliance Analysis

The third step is the first main result of this paper i.e. compliance measure between $P_{\text{Desired}}$ and $P_{\text{Actual}}$. It is at this stage that unsatisfactorily performing units are clearly differentiated from the satisfactorily performing ones. This is accomplished by measuring the standard correlation between $P_{\text{Desired}}$ and $P_{\text{Actual}}$ over a given time window. The approach is flexible since it is dependent on the windowing scheme. For example, one may be interested in a single 24-hour correlation value as opposed to a multi-valued correlation interpretation representing a segmentation of the whole 24-hour interval. With the first method, consistently poorly performing units will be easily identified while intermittent poorly performing units will best be characterized with the second method. An even more descriptive quantification will be through the use of a moving window, where one can investigate the time varying nature of the correlation between $P_{\text{Desired}}$ and $P_{\text{Actual}}$.
So, for a given windowing scheme, a unit with a high correlation value will be considered as having complied well to the P\textsubscript{Desired} signal, while one with a low value, that may be below a predetermined threshold value, will be considered as having failed the necessary requirements of AGC compliance. Of course, this threshold is dependent on the above-mentioned windowing schemes. In this paper, the first method is used. Equations below show the calculation for the standard correlation coefficient used in this analysis.

\[ C = E\{ (P_{\text{Desired}} - \bar{P}_{\text{Desired}})(P_{\text{Actual}} - \bar{P}_{\text{Actual}}) \} \]  
\[ \sigma_{\text{Desired}} = \sqrt{\frac{\sum_{1}^{n} (P_{\text{Desired}} - \bar{P}_{\text{Desired}})^2}{n(n-1)}} \]  
\[ \sigma_{\text{Actual}} = \sqrt{\frac{\sum_{1}^{n} (P_{\text{Actual}} - \bar{P}_{\text{Actual}})^2}{n(n-1)}} \]  
\[ r = \frac{C}{\sigma_{\text{Desired}} \sigma_{\text{Actual}}} \]

where \( n \) is the number of samples for a given window, \( C \) is the expectation value of the product of deviation from mean values \( \bar{P} \), \( \sigma \) is the standard deviation and \( r \) is the correlation coefficient.

### 3.4 Unit Transfer Function

In the fourth and final stage, a unit’s transfer function is identified. Figure 3.3 below shows the input-output identification process diagram performed in the paper. This transfer function models the relationship between \( P_{\text{Desired}} \) and \( P_{\text{Actual}} \). To accomplished this, two subtasks must be completed:

a) Selection of model type and order  
b) Identification of model parameters

In both cases, the appropriate window sizes selected for analysis has a large effect on the result. In other words, a certain model that behaves well over a certain interval does not necessarily mean it performs well over a shorter or longer interval. As stated in the previous section, when an acceptable transfer function is obtained, a user may apply it for use in planning unit responses to an arbitrary set of desired signals. This also can provide participants extra information in its bidding scheme.

Signal Processing Toolbox from Mathworks is applied in this study. Three different model types are used, specifically

a) Autoregressive Exogenous (ARX):
\[ A(q)P_{\text{Actual}}(t) = B(q)P_{\text{Desired}}(t - nk) + e(t) \]  
\[ (3.10) \]

b) Autoregressive Moving-Average Exogenous (ARMAX):
\[ A(q)P_{\text{Actual}}(t) = B(q)P_{\text{Desired}}(t - nk) + C(q)e(t) \]  
\[ (3.11) \]

c) Box-Jenkins (BJ):
\[ P_{\text{Actual}}(t) = \frac{B(q)}{F(q)}P_{\text{Desired}}(t - nk) + C(q)e(t) \]  
\[ (3.12) \]

In these equations, the notation definitions are:
- \( q \)- shift operator  
- \( nk \) - embedded model delay  
- \( na, nb, nc, nd, nf \) - order of corresponding polynomials \( A(q), B(q), C(q), D(q) \) and \( F(q) \) respectively. While \( nb-1 \) is the order of \( B(q) \). \( e(t) \) is a zero mean gaussian distributed white noise model.

\[ A(q) = 1 + a_1q^{-1} + ... + a_{na}q^{-na} \]  
\[ B(q) = 1 + a_1q^{-1} + ... + a_{nb-1}q^{-nb+1} \]  
\[ C(q) = 1 + c_1q^{-1} + ... + c_{nc}q^{-nc} \]  
\[ D(q) = 1 + d_1q^{-1} + ... + d_{nd}q^{-nd} \]  
\[ F(q) = 1 + f_1q^{-1} + ... + f_{nf}q^{-nf} \]

More detail work on the method can be accessed from [9].

Thus, based on the selected model, the window size and input-output data, \( P_{\text{Desired}}(t) \) and \( P_{\text{Actual}}(t) \) respectively, a new set of data is generated. We define it as \( P_{\text{ARX}}, P_{\text{ARMAX}} \) or \( P_{BJ} \). Having developed the model signal, statistical analysis is performed to calculate the mean error between the model output and the actual output from

\[ \end{align*} \]
the generator. This will provide us with a direct indication of accuracy of the model or equations from (3.10-3.12).

4. SIMULATION RESULT

4.1 Compliance

Below are some of the results from the analysis.

Table 4.1 Compliance metrics for a pass/fail process in a 5-hour window

<table>
<thead>
<tr>
<th>UNIT</th>
<th>r</th>
<th>Pass/Fail</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>0.1018</td>
<td>F</td>
</tr>
<tr>
<td>A2</td>
<td>0.0657</td>
<td>F</td>
</tr>
<tr>
<td>A3</td>
<td>0.9408</td>
<td>P</td>
</tr>
<tr>
<td>B1</td>
<td>0.8711</td>
<td>P</td>
</tr>
<tr>
<td>B2</td>
<td>0.8767</td>
<td>P</td>
</tr>
<tr>
<td>C1</td>
<td>0.7285</td>
<td>P</td>
</tr>
<tr>
<td>C2</td>
<td>0.7673</td>
<td>P</td>
</tr>
<tr>
<td>C3</td>
<td>0.8351</td>
<td>P</td>
</tr>
<tr>
<td>C4</td>
<td>0.8793</td>
<td>P</td>
</tr>
</tbody>
</table>

Based on Table 4.1, the values of the correlation coefficients between the $P_{\text{Desired}}$ and $P_{\text{Actual}}$ are presented. The table shows that units A1 and A2 perform disappointingly. This is indicated in the table as F, meaning that the results fail to comply with $P_{\text{Desired}}$. The other units passed the test and are marked as P. In this paper, we adopted 0.5 as the threshold point for passing, which 1 constitutes excellent compliance and 0 a total failure. Figure 4.1 and 4.2 show a comparison between $P_{\text{Desired}}$ and $P_{\text{Actual}}$ for the cases of poor and good compliance, respectively.

4.2 Transfer Function

For the transfer function analysis, only those units that passed the compliance test are considered. Using the ARX model (3.10), we obtained the following transfer function for unit C4. The s-domain (Laplace Transform) representation is

$$H(s) = \frac{0.1118s^3 - 0.7648s^2 + 0.2077s + 1.12}{s^9 - 0.3131s^8 - 0.169s^7 + 0.2306s^6 - 0.06779s^5}$$

This transfer function is derived by selecting the window size to be 5-minutes. In this case (i.e. window size and model order), the two other model types (ARMAX and BJ) yielded very large errors so we ignored them. Figure 4.3 shows the model output comparison with $P_{\text{Desired}}$ and $P_{\text{Actual}}$. The mean error between the model and the actual is merely 0.6 MW, which is considered excellent in this case.

5. CONCLUSION

In the ancillary market, regulation is a prime commodity. Based on available data, the quality of regulation varies from unit to unit. From a system operator’s viewpoint, a means of identifying poor performing regulating units is very important. In addition, an index to quantify how well a good unit regulates will also be helpful in terms of affecting pricing schemes. This paper introduces a scheme that accomplishes both tasks. In addition a scheme to derive a transfer function representation of a units regulation behavior is also provided. Such a function can be used by various interested parties to quantify a unit’s response to an arbitrary set of regulation signals. Future work will concentrate on identifying optimal windowing schemes that affect all three tasks:

a) Identification of poor performing regulating units
b) Quantification of compliance
c) Transfer function determination
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7. REFERENCES