Creation of Synthetic Electric Grid Models for Transient Stability Studies

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Abstract—Test cases are widely used in the power system transient stability area for teaching, training, and research purposes. Even though several small-scale test cases are available to the public, access to actual large-scale power system models is more limited. Synthetic network modeling methodology has addressed this issue and aims to generate test systems that are completely fictitious but capable of representing characteristic features of actual power grids. Previous work has proposed an automated algorithm to create synthetic transmission network base models, with statistics similar to those of actual power grids. This paper presents an approach to extend synthetic network base models for transient stability studies. Statistics summarised from actual models are the bases in assigning appropriate models with proper parameters to each synthetic generator. A model validation and tuning process is also proposed. The construction of dynamic cases for two synthetic network models is presented as illustrations.

Index Terms—power system transient stability, synthetic networks, generator dynamics, model validation

I. INTRODUCTION

Transient stability in power systems refers to the ability of a synchronous power system to return to stable conditions and maintain its synchronism following a relatively large disturbance [1], [2]. There are relatively few publicly available power system models for transient stability studies. For example, six models are presented in [3] with number of buses (generators) ranging from 6 (3) to 68 (16). All those models are completely fictitious or high-level summaries of actual grid models. A group of researchers have also extended and archived IEEE test systems with dynamic model data appropriate for performing time-domain simulations [4], [5]. European Network of Transmission System Operators for Electricity and the University of Erlangen-Nuremberg collaborated to create a dynamic study model of the entire continental Europe power system. Even though the dynamic study model of the entire continental Europe power system is documented in [6], the access to the data is restricted. Actual large-scale power system models are used to simulate system frequency response so as to provide realistic, insightful results on power system transient stability [6]–[8]. However, legitimate security concerns severely limit the disclosure of information about actual system models. The lack of full public access to actual power system models limits the global power system community’s ability to engage in research related to power system transient stability. Several test cases with dynamics are available to the public, but there is limited access to actual large-scale power system models that represent the complexity of today’s electricity grids for dynamic studies. As such, this paper addresses the need to build synthetic large-scale system dynamic models for transient stability studies.

Synthetic networks have no relation to the actual electric grid in their geographic location, thus they pose no security concern and are publicly available for comparing results among researchers. This paper builds on previous works [9], [10] to extend a synthetic network base case with generator dynamics. The proposed approach applies statistics summarised from one North American Eastern Interconnection (EI) case to assign appropriate parameters to generators. For each model (machine, governor, exciter, and/or stabilizer), we categorize model parameters into two groups with discretely or continuously distributed parameters. Typical values for each discrete parameter are assigned to synthetic generators in probabilities proportional to total capacity of actual generators, adopting those values in the EI case. As for a continuous parameter, a value is statistically selected from its possible range obtained from actual models and assigned to a synthetic generator. Model validation and parameter tuning procedure is then proposed to adjust model parameters such that each parameter value is reasonable and each model has satisfactory test performances. Generator cost models are also included in the way described in [11] for unit commitment and economic dispatch purposes. The proposed approach is applied to build 200-bus and 500-bus test cases on the footprint of the central Illinois and South Carolina, respectively. All synthetic network cases are available at [12].

In this paper, four more sections come as follows. In Section II, an algorithm is developed to automatically complete the parameter determination for adding dynamics to each synthetic generator. Model validation and tuning process is proposed in Section III. Section IV provides illustrative examples, and Section V concludes this paper and provides future work direction.

II. EXTENSION OF SYNTHETIC NETWORK BASE MODELS WITH GENERATOR DYNAMICS

Each generator in a synthetic network base model has its generation capacity and fuel type defined in the network building process. These two are the basic parameters to add
synthetic dynamic models of synthetic generators’ machine, turbine-governor, exciter, and/or stabilizer models. This section focuses on determining appropriate model parameters, as briefly shown in Fig.1, and then presents detailed statistical analysis on selected machine / governor / exciter / stabilizer models.

Fig. 1. Statistical extension process to include generator dynamic models

A. Statistical Extension Process

For each discrete parameter, we are interested in those values that appear much more frequently than others in actual system models. One value is defined as “dominant” if the percentage of models adopting that value is over some threshold value. For any model \( m \), each discrete parameter may have multiple dominant values, which are assigned to synthetic generators equipped with model \( m \) by probabilities proportional to their relative percentages.

Some parameters have discrete distributions while others are continuous. A possible range of values for each continuous parameter is found based on statistics summarized from actual system models. For any model \( m \) with a continuous parameter \( c \), values are statistically selected from \( c \)’s possible range and assigned to synthetic generators equipped with model \( m \).

Some parameters depend on fuel type and/or generator capacity, and some other parameters have strong correlations. Such relationships are also summarized from actual power system models and used to facilitate parameter assignment procedure. For instance, given any model \( m \) with two strongly correlated continuous parameters \( c_1 \) and \( c_2 \), one value for \( c_1 \) is statistically determined first and the remaining one \( c_2 \) is assigned a value computed using \( c_1 \) value and their correlation observed in actual system models.

Additionally, there are physical limitations on statistically assigning values to model parameters. Those limitations are used to exclude combination of model parameters. For example, in the GENROU model, \( X''_d < X'_q \) and \( X'_d > X_I \) should be enforced as hard constraints.

Here, we use coal-fueled power plants as an illustrative example and only consider one typical model for machine(GENROU), governor(TGOV1) and exciter(SEXS).

B. Machine Model - GENROU

Fig.2 shows the block diagram for the machine model GENROU. As observed in Fig.3, the machine inertia value depends on the generator capacity. The line encloses the region where possible inertia values are drawn from for coal units. For instance, if a synthetic generator has a 500-MW generation capacity, an inertia value is statistically picked from the range [2,4].

Fig. 2. Block diagram for machine model GENROU

Fig. 3. Dependence of machine inertia on generator capacity for coal units

Next we determine values for \( X_d, X_q, X'_d, X'_q, X''_d \) and \( X_I \). Three well-fit linear regressions are found for \( X_d \) and \( X_q, X'_d \) and \( X_I \), as well as \( X''_d \) and \( X'_q \) (as displayed in Fig.4(a)-(c)). Statistical analysis also shows the dependence of \( X''_d \) on \( X_d \) and \( X'_q \) on \( X_q \) (as displayed in Fig.4(d)-(e)). Till now, with three linear relations and two statistical dependences, only one value among \( X_d, X_q, X'_d, X'_q, X''_d \) and \( X_I \) is needed to determine all their values. This sub-section starts with the dependence of \( X_d \) on generator capacity for coal units (as displayed in Fig.4(f)). For instance, given a 500-MW coal plant:

- Based on Fig.4(f), we statistically draw a value from [1.60, 2.33] for \( X_d \);
- Based on Fig.4(a) and the value \( X_d \), we apply the observed linear relation to determine a value for \( X_q \);
- Based on Fig.4(d), we statistically draw a value from a possible range conditioned on the value \( X_d \) for \( X'_d \);
- Based on Fig.4(e), we statistically draw a value from a possible range conditioned on the value \( X_q \) for \( X'_q \);
Based on Fig.4(c) and the value $X'_d$, we apply the observed linear relation to determine a value for $X''_d$;
Based on Fig.4(b) and the value $X''_d$, we apply the observed linear relation to determine a value for $X_l$.

**Fig. 4.** Statistics on $X_d$, $X_q$, $X'_d$, $X'_q$, $X''_d$ and $X_l$ in the GENROU model for coal units

We present in Table.I the correlation analysis results on time constants - $T'_do$, $T'_qo$, $T''_do$ and $T''_qo$. The cumulative distribution functions (c.d.f.s) of four time constants are shown in Fig.5. A similar statistics-based approach is used to determine values of four time constants for synthetic generators.

**TABLE I**

<table>
<thead>
<tr>
<th>Time Constant</th>
<th>$T'_do$</th>
<th>$T'_qo$</th>
<th>$T''_do$</th>
<th>$T''_qo$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T'_do$</td>
<td>1.0000</td>
<td>0.5766</td>
<td>-0.0255</td>
<td>-0.0098</td>
</tr>
<tr>
<td>$T'_qo$</td>
<td>0.5766</td>
<td>1.0000</td>
<td>-0.0135</td>
<td>0.0774</td>
</tr>
<tr>
<td>$T''_do$</td>
<td>-0.0255</td>
<td>-0.0135</td>
<td>1.0000</td>
<td>0.1336</td>
</tr>
<tr>
<td>$T''_qo$</td>
<td>-0.0098</td>
<td>0.0774</td>
<td>0.1336</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

As shown in Fig.6(a), for the saturation functions, a linear regression $S_{12} = 1.9988S_1 + 0.2355$ (with R-squared value to be 0.8) is observed and then used in the parameter assignment process. The c.d.f in Fig.6(b) is applied to statistically draw a value from the range [0.02,0.2] for $S_1$.

**Fig. 6.** Statistics on saturation function coefficients in GENROU model for coal units

**C. Governor Model - TGOV1**

**Fig.7** shows the block diagram for the turbine-governor model TGOV1. The TGOV1 model is a simple steam turbine model and represents the turbine-governor droop ($R$), the main steam control valve motion and limits ($T_1$, $V_{MAX}$, $V_{MIN}$) and has a single lead-lag block ($T_2$, $T_3$) representing the time constants associated with the motion of the steam through the reheater and turbine stages. The ratio, $T_2/T_3$, equals the fraction of the turbine power that is developed by the high-pressure turbine stage and $T_3$ is the reheater time constant. $D_t$ is the turbine damping coefficient.

**Fig. 7.** Block diagram for the governor model TGOV1

Since TGOV1 is the simplest governor model and many other models are built on or extended from TGOV1 by adding more details [13], we collect statistics (on on $T_1$, $T_2$, $T_3$, $R$, $V_{MAX}$, $V_{MIN}$ and $D_t$) from TGOV1 and some other governor models for coal units to add parameter variations. Fig.8 summarizes the statistics on $T_1$, $T_2$, $T_3$ and $R$ of TGOV1 model for coal units. As such, a constant value 0.05 is set for $R$. Two values - 0.5 and 0.2 - are assigned to $T_1$ by probabilities of 0.6 and 0.1, respectively, while the remaining 30% of $T_1$ are statistically drawn from [0.1,0.5]. $T_2/T_3$ ratio has two typical values: 0.3 (about 70%) and about 0.3333 (about 20%). In addition, $T_2/T_3$ ratio value distribution has trivial correlation with $T_2$ or $T_3$. Thus, we statistically assign 0.3 and 0.3333 as the $T_2/T_3$ ratio to TGOV1 models by probabilities of 0.77 and 0.23, respectively. Around 80% of $T_2$ equals to either 2.1(44%), 2.5(11%) or 3 (25%). We statistically assign 2.1, 2.5 and 3 to TGOV1 models by probabilities of 0.55, 0.13 and 0.32, respectively. $T_1$ is not statistically correlated with $T_2$ and
Thus, the three assignments can be performed individually. Last, $V_{MAX}$ is set to 1 since over 90% of studied models in the EI model have $V_{MAX}$ of 1 and $V_{MIN}$ is set to 0 since over 90% of studied models in the EI model case $V_{MIN}$ of 0. Over 95% of $D_t$ of studied models in the EI case is 0, thus the $D_t$ in the synthetic case is set to 0.

The parameter assignment process works in a way similar to those in Sections II.A and II.B. According to Fig.10(a), 35% of synthetic SEXS models are assigned with $K=100$, 20% are assigned with $K=200$, 20% are assigned with $K=250$, and the remaining 25% are assigned with values uniformly drawn from [100,200]. Similarly, we assign about 50% of synthetic SEXS models with $T_E=0.02$, 35% of them with $T_E=0.05$ and the remaining to have $T_E=0.1$. Except value of zero, there are about 2/3 models with $T_A/T_B=0.1$ and 1/3 of them with $T_A/T_B=0.125$. Thus, we statistically assign 0.1 and 0.125 to $T_A/T_B$ by probabilities of 0.67 and 0.33, respectively. 10 and 8 are assigned to the $T_B$ values by probabilities of 0.75 and 0.25, respectively. This is because 10 (around 58%) and 8 (around 21%) are two most common values for $T_B$.

III. MODEL TUNING AND VALIDATION

Section II describes a prototype procedure to extend initial synthetic network models with generator dynamics. The statistical parameter assignment procedure aims to match statistics from actual models, followed a model validation and tuning process discussed in this section.

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$E_{FDMIN} = -4$ ($E_{FDMAX} = 5$) is considered since over 80% (86%) of models in the EI case have $E_{FDMIN}$ of −4 ($E_{FDMAX}$ of 5).

Each machine with its control elements needs to meet specified performance criteria in designed tests [13]–[17].
For excitation systems, frequency responses of the automatic voltage regulator control loop are of primary interest [14], [17]. Both open-loop and closed-loop frequency responses are useful for assessing the performance of feedback control systems. Typical open-loop and closed-loop frequency responses of an excitation control system with the synchronous machine open-circuited are shown in Fig.11.

Relative stability of a feedback control system is measured in terms of the gain and phase margins. In this paper, an excitation control system with a gain margin above 6 dB and a phase margin above 40° is used. In addition, the bandwidth \( \omega_B \), the peak value \( M_p \) (a measure of relative stability.) of the gain characteristic, and the frequency \( \omega_c \) at the peak value \( M_p \) are usually selected as the closed-loop frequency response characteristics. For a well-designed excitation control system, \( 1.1 < M_p < 1.6 \) is preferred.

Both open-loop and closed-loop frequency responses are evaluated for each generator. Given a generator that does not meet at least one of the recommended performance criteria:

- If a violation is small, some exciter parameters are changed by a manual adjustment process;
- If a violation is significant, we re-run the parameter process proposed and re-validate/tune the generated parameters.

IV. ILLUSTRATIVE EXAMPLE

Once the synthetic network base models with buses, generators, loads, transformers, and transmission lines, have a feasible ac power flow solution, the proposed approach is applied to improve the realism of those models by including data necessary for transient stability studies. For illustrations, this section presents two synthetic network dynamic cases, which are available at [12].

A. ACTIVSg200 Case

This section provides results for a 200-bus case with two voltage levels (230/115 kV) on the footprint of Central Illinois. As shown in Fig.12, this case represents one single area covering fourteen counties and 1.1 million people. This case contains 49 generators with a total capacity of 3543 MW and the load level is set at 2229 MW and 653 MVar. This case has a flat start with well-damped and stable performance in selected N-1 contingencies (loss of generation or three-phase fault at one bus). Some transient stability simulation results are displayed in Fig.13.

B. ACTIVSg500 Case

As shown in Fig.14, the second case is built on the footprint of the western South Carolina, which covers about 21 counties and serves around 2.6 million people. 90 generators in this case have a total capacity of 12188 MW. The synthetic system has two voltage levels (345/138 kV). Extensive simulations will be performed to verify that this case has a flat start with well-damped and stable performance in selected N-1 contingencies (loss of generation or three-phase fault at one bus). Compared to the previous 200-bus model with simply GENROU, TGOV1 and SEXS (all statistical analyses are performed on coal units), modeling dynamics for ACTIVSg500 case are different in two aspects:

- Three fuel types are considered when modeling dynamics - coal, gas and hydro - with no wind in this case and all other units treated as coal units;
- A fixed set of machine, exciter and governor models with various parameters: coal - GENROU, TGOV1, SEXS; gas - GENROU, GAST, SEXS; hydro - GENROU, HYGOV, SEXS. Statistical analysis is performed individually for each fuel type.

Simulation results for a loss of 445-MW generation and a three-phase fault at bus 225 are displayed in Fig.15.
V. Conclusion

This paper has presented a methodology for the creation of synthetic electric grid models for use in transient stability studies. Detailed statistical analysis performed on selected machine / governor / exciter / stabilizer models is presented to illustrate the statistical extension process to include generator dynamic models. Model validation and tuning process for excitation control systems is introduced to verify and properly modify the obtained model parameters. The synthetic dynamic models can be used for power system planning, generator siting and other applications related to power system transient stability.

The proposed method is general enough to consider multiple fuel types and various models for each fuel type. Although this paper uses two specific footprints to illustrate the synthetic network creation process, the proposed methodology is general enough for applications to other footprints of interest. The developed synthetic networks with dynamic models can enable research using large-scale cases available publicly.

REFERENCES


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