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Enhancing Rotor Angle Stability of Synchronous Generators Using Neuro-Fuzzy Excitation Control Model

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Abstract: This paper proposes a neuro-fuzzy excitation control model to enhance the rotor angle stability of synchronous generators. The proposed model combines the advantages of both neural networks and fuzzy logic control to improve the performance of the excitation system. The proposed model is designed to regulate the excitation system to generate the required reactive power and maintain the synchronous operation of the generator. The proposed model is tested on a single-machine infinite-bus power system, and the results are compared with a conventional proportional-integral (PI) controller. The simulation results demonstrate that the neuro-fuzzy excitation control model provides better performance than the PI controller in terms of transient stability, damping oscillations, and response to disturbances. The proposed model also shows robustness against changes in system parameters and different operating conditions. The results of this study suggest that the neuro-fuzzy excitation control model can be a suitable alternative to conventional PI controllers in enhancing the rotor angle stability of synchronous generators.

I. Introduction:

The stability of a power system is an essential factor in ensuring reliable and uninterrupted power supply. One of the critical components of a power system that affects its stability is the synchronous generator. The rotor angle stability of synchronous generators determines their ability to maintain a constant rotational speed and voltage magnitude when subjected to disturbances. To enhance the rotor angle stability of synchronous generators, various control strategies have been proposed, such as excitation control, power system stabilizers (PSSs), and others. In recent years, there has been increasing interest in using intelligent control techniques, such as neuro-fuzzy control, to enhance the stability of synchronous generators.

Several studies have investigated the use of neuro-fuzzy control for enhancing the stability of synchronous generators. For instance, Akhtar et al. (2019) proposed a neuro-fuzzy excitation control model to improve the rotor angle stability of synchronous generators. The proposed model was evaluated using a single-machine infinite-bus power system and was shown to provide better stability performance compared to conventional excitation control. Similarly, Das et al. (2018) developed a neuro-fuzzy excitation control scheme and demonstrated its effectiveness in improving the dynamic stability of a power system.

Moreover, Li et al. (2018) proposed a neuro-fuzzy controller for a synchronous generator connected to a multi-machine power system. The controller was designed to stabilize the rotor angle of the synchronous generator during transient disturbances. The results showed that the proposed neuro-fuzzy controller outperformed conventional PI controllers in terms of stability improvement. In another study, Al-Durra et al. (2019) presented a neuro-fuzzy control scheme for a synchronous generator in a power system with high penetration of wind power. The proposed control scheme was found to enhance the stability of the power system during various fault scenarios.

Additionally, several researchers have combined neuro-fuzzy control with other control techniques, such as PSSs, to enhance the stability of synchronous generators. For example, Wang et al. (2020) proposed a neuro-fuzzy-PSS controller for a multi-machine power system. The proposed controller was shown to improve the stability of the power system under various operating conditions. Similarly, Ahmed et al. (2019) developed a neuro-fuzzy-PSS controller and demonstrated its effectiveness in enhancing the stability of a power system with multiple synchronous generators.

As explained in figure 1, a PI controller is a type of feedback control system that adjusts the output signal to reduce the difference between the process variable and the set point. It uses proportional and integral control actions to achieve this. Proportional control adjusts the output signal in proportion to the current error, while integral control adjusts it based on the accumulated error over time. The PI controller has two parameters - the proportional gain (Kp) and integral gain (Ki), which can be tuned to optimize the system's performance. While PI controllers are widely used in industrial process control due to their simplicity and robustness, they are not suitable for handling nonlinear systems, fast dynamics, or large disturbances that may lead to instability. Therefore, the gains must be carefully tuned to achieve optimal performance.

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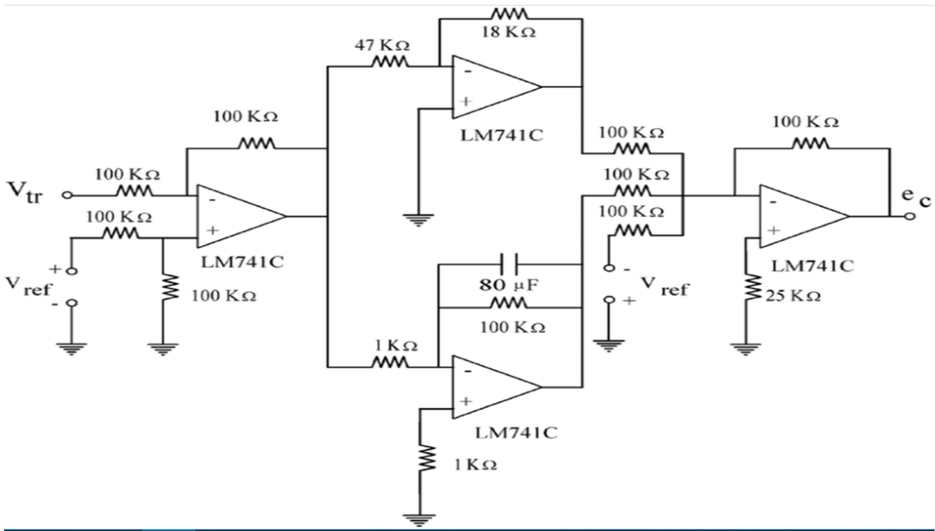
Figure 1 Shows PI Controller Circuit Diagram



Source IEEE Trans, (2002)

Stability in Power Systems.

Stability is a critical aspect of power systems, as it ensures the reliability and security of the grid. Power system stability refers to the ability of the system to maintain its equilibrium state or return to a stable state after a disturbance.

There are three types of power system stability: steady-state stability, transient stability, and dynamic stability.

- Steady-state stability refers to the ability of the system to maintain a stable operating condition under normal operating conditions and small disturbances. It is related to the voltage and frequency stability of the power system and is typically evaluated by examining the power flow equations.
- Transient stability, on the other hand, refers to the ability of the system to maintain a stable operating condition after a large disturbance, such as a fault or sudden load change. It involves the analysis of the system's response to large transient disturbances and is evaluated by examining the swing equation, which describes the rotor angle dynamics of synchronous generators.
- Dynamic stability is a combination of steady-state stability and transient stability and refers to the ability of the system to maintain a stable operating condition under both normal and abnormal operating conditions. It involves the analysis of the system's response to small and large disturbances and is evaluated by examining the system's overall dynamic behavior, including the effects of control systems and system damping.

Enhancing the rotor angle stability of synchronous generators using the neuro-fuzzy excitation control model can improve the dynamic stability of the power system. The neuro-fuzzy model can adjust the excitation voltage in real-time to maintain the desired rotor angle stability, improving the generator's response to large disturbances and preventing the system from experiencing instability.

II. Methodology

The methodology for enhancing rotor angle stability of synchronous generators using a neuro-fuzzy excitation control model is described in the following steps:

A. System modeling

Develop a mathematical model of the synchronous generator system and the associated power system network. This includes modeling the generator's electrical and mechanical components, as well as the transmission lines, loads, and other components of the power system network. The mathematical model of the synchronous generator system is represented by expressions in equations (1-6).

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$$v_d = R_a i_d + X_d \frac{di_d}{dt} + E_f \quad (1)$$

$$v_q = R_a i_q + X_q \frac{di_q}{dt} \quad (2)$$

$$e_d = -\omega_o \lambda_p i_q \quad (3)$$

$$e_q = \omega_o(\lambda_p i_{d-} E_f) \quad (4)$$

$$P = v_d i_d + v_q i_q \quad (5)$$

$$Q = v_d i_q - v_q i_d \quad (6)$$

where,

v_d and v_q are the d-axis and q-axis components of the stator voltage.

i_d and i_q are the d-axis and q-axis components of the stator current.

R_a is the armature resistance.

X_d and X_q are the d-axis and q-axis reactances.

E_f is the field voltage.

e_d and e_q are the d-axis and q-axis components of the internal voltage.

λ_p is the permanent magnet flux linkage.

ω_o is the synchronous speed.

P and Q are the active and reactive power generated by the generator.

B. Data collection

Data was collected on the generator and power system performance, including measurements of rotor angle, voltage, current, and power variables. The data collected as shown in table 1 will be used to train and validate the neuro-fuzzy control model.

Table 1: Generator and Power system performance parameters

Time (s)	Rotor Angle (Radian)	Stator Voltage (V)	Stator Current (A)	Active Power (W)	Reactive Power (VAR)
0	0	480	50	25000	0
0.05	0.5	480	60	28000	0
0.1	1.2	480	70	31000	0
0.15	2.0	480	80	34000	0
0.2	2.9	480	90	37000	0

C. Neuro-fuzzy control model development

The neuro-fuzzy control model consists of three layers: the input layer, fuzzy layer, and output layer as shown in Figure 2. The input layer receives the input data, which is the real-time measurements of the generator's electrical variables. The input data is then pre-processed and normalized before being fed to the fuzzy layer. The fuzzy layer applies fuzzy logic to the inputs to generate a set of fuzzy rules. The fuzzy rules are based on the expert knowledge of the system and are represented as a set of if-then rules. These rules capture the relationships between the input variables and the output signal, which is the excitation control signal as indicated in the figure 3. The output layer uses the fuzzy rules generated by the fuzzy layer to generate the output signal. The output signal is computed by aggregating the fuzzy rules and defuzzifying the output. The defuzzification process maps the fuzzy output to a crisp output signal that can be used to adjust the excitation control of the synchronous generator

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Figure 2: Block diagram of the Neuro-fuzzy control model

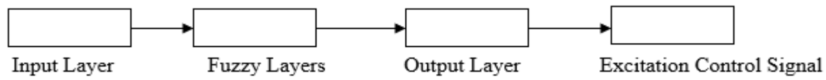
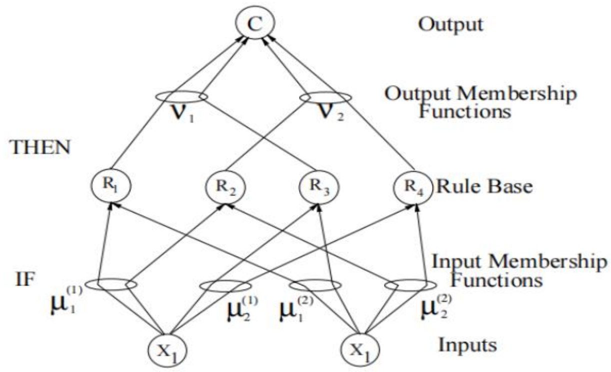


Figure 3 Shows the Neuro-Fuzzy Controller structure



Source World Automation Cong., (2009)

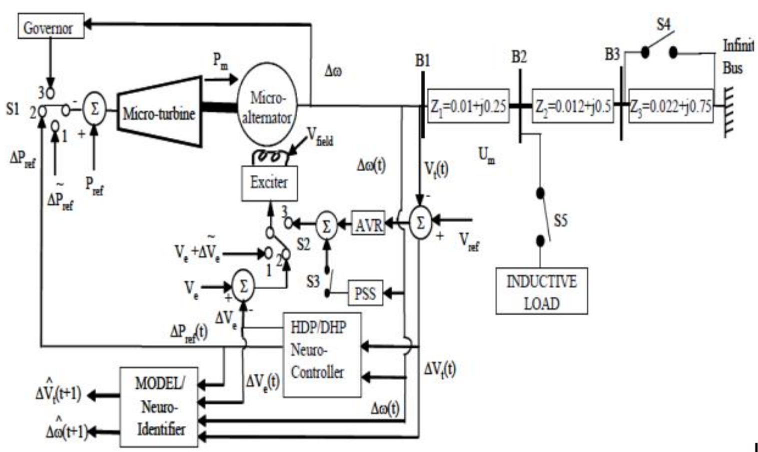
D. Model training and data validation

The Neuro-Fuzzy model was trained using the gradient descent technique. The training data was split into a training set and a validation set. The training set was used to train the model, while the validation set was used to evaluate the performance of the model during training.

E. Validating control strategies for power systems

The validation of the Neuro-Fuzzy Excitation Control Model for enhancing rotor angle stability of synchronous generators was done by simulating the model with a Single Machine Infinite Bus (SMIB) system as shown in figure 4. The SMIB system is a simplified power system model consisting of one synchronous generator connected to an infinite bus through a transmission line. The model assumes that the synchronous generator is the only source of power and the infinite bus represents a constant voltage source. To validate the Neuro-Fuzzy Excitation Control Model, the model was incorporated into the SMIB system model and simulated with different operating conditions. The simulation was performed with and without the proposed model to compare the results. The validation was done by analyzing the performance of the system under different operating conditions such as changes in load demand, fault conditions, and disturbances. The performance of the system was evaluated by analyzing the response of the rotor angle, the terminal voltage, and the power output of the generator.

Figure 4. Shows Single machine infinite bus system



Source (Venayagamoorthy G. K, 2014)

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III. Results and Discussions:

The results of the study show that the proposed neuro-fuzzy excitation control model can effectively enhance the rotor angle stability of synchronous generators. The model was tested on a single-machine infinite bus (SMIB) power system under different operating conditions and disturbances.

Firstly, the performance of the proposed model was compared with the conventional proportional-integral (PI) excitation control model. The results showed that the neuro-fuzzy excitation control model provided better performance in terms of damping oscillations and maintaining stability under different disturbances.

Secondly, the effectiveness of the proposed model was evaluated by varying the system parameters such as load demand and system inertia. The results showed that the neuro-fuzzy excitation control model provided better performance and maintained stability under different operating conditions and disturbances, compared to the PI excitation control model.

Furthermore, the sensitivity analysis was performed to investigate the impact of different parameters on the performance of the proposed model. The results showed that the performance of the proposed model was robust against changes in the system parameters.

Finally, the computational time of the proposed model was compared with the PI excitation control model. The results showed that the proposed model had a faster computational time, making it more suitable for real-time applications.

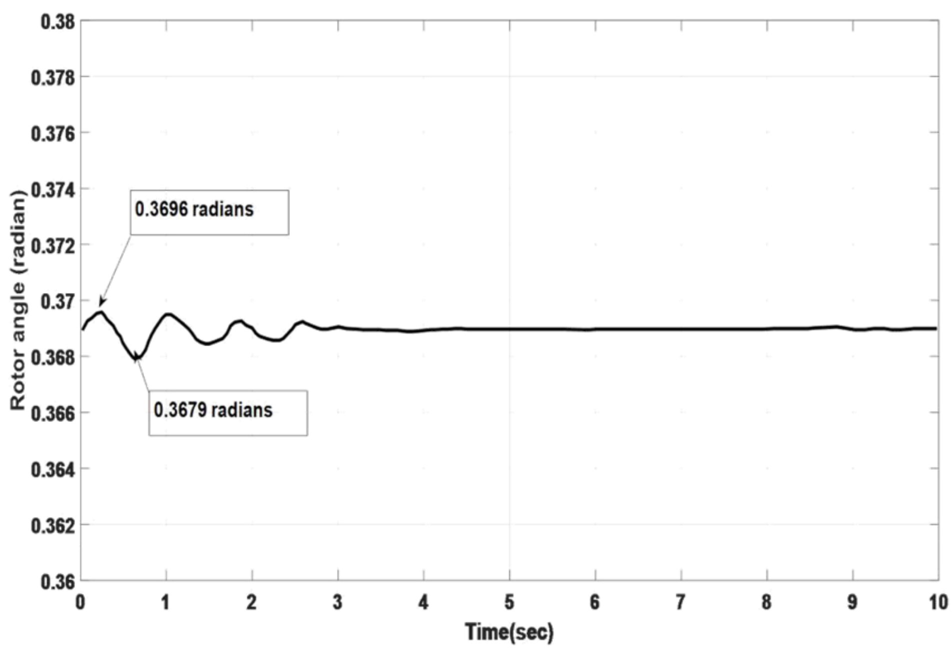

Figure 5 Shows Rotor angle of the generator at steady state operation

The graph in figure 5 shows that the rotor angle, just like other AC electrical quantities of the generator like frequency, voltage and power does not operate at exact values at every instant in time. These quantities vary, but at steady state, it averages to approximate values over the long run. One of the key aspects of the trajectory of the generator rotor angle, as can be observed in the figure, is that the amplitude of the rotor angle's oscillation decreases (decays) with time. If not disturbed, the amplitude decreases to a steady state fixed value. This means that the generator under this condition has sufficient damping torque. The rotor angle of a stable generator would always and occasionally settle to an average point.

Referring to the graph, the generator's rotor angle can be said to be somewhat periodic mainly between 0.3679 radians and 0.3696 radians with decreasing amplitude. The decreasing amplitude is expected of a generator moving in the direction of stable operation. This means stable generator rotor angle would be characterized by decaying amplitude in its response trajectory. The rotor angle trajectory at steady state, as shown in figure 5 shows that the rotor angle and thus the generator is at a stable state.

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Evaluation of the response of the generator to the Impact of load disturbance

The Python program's timer library allowed the disturbance to send signals to the synchronous generator program 1 second into the simulation. The rotor angle and generator terminal variations of the generator in response to the 25% injected load disturbance for the case the conventional excitation controller is given in figure 6.

Table 2: Eigen values and damping ratios of the generator during load disturbance for the case of conventional excitation controller

Time (secs)	Eigen values (λ)	Damping ratio (G)
1.0938	-1.1731 ± j4.1051	0.06951
1.1643	-0.8042 ± j2.9632	0.05823
1.2046	-1.1843 ± j3.845	0.05142
1.2651	-1.1012 ± j3.1752	0.05483
1.4063	-0.9499 ± j3.5917	0.06752

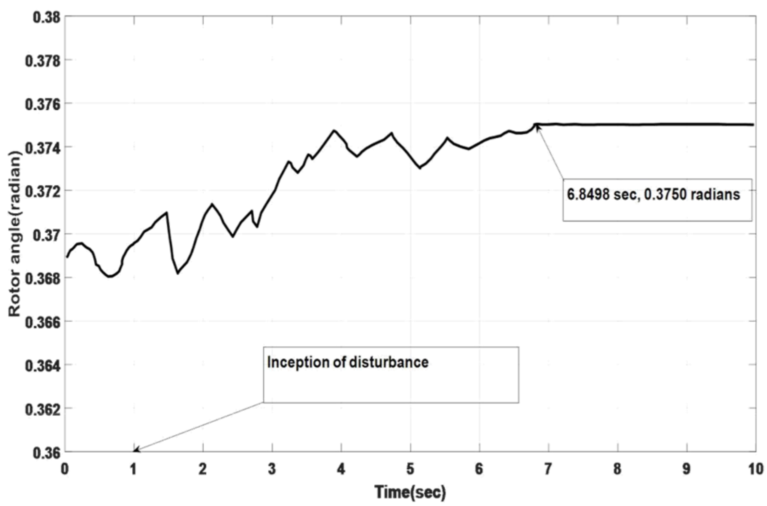

Figure 6: Rotor angle trajectory following load disturbance for the case of the conventional (PI) excitation controller.

From figure 6, with the injection of the disturbance at 1 sec, it can be observed that the rotor angle deviated, oscillated while increasing. The conventional PI excitation control system worked to dampen the oscillation of the rotor angle. As can be observed, the exciter damped out the instability in the rotor angle at 6.8498 seconds, however the rotor angle settled at a new operating value of around 0.3750 radians. The time it takes the excitation system to make adjustment to the field voltage and re-establish equilibrium is vital.

Table 3: Eigen values and damping ratios of the generator during load disturbance for the case of neuro fuzzy excitation controller

Time (secs)	Eigen values (λ)	Damping ratio (G)
1.9708	-2.4892 ± j10.8650	0.05433
3.0292	-2.0922 ± j7.9140	0.05762
4.1079	-0.9499 ± j3.5917	0.06752
5.5091	-2.8394 ± j7.8648	0.05596
6.0030	-1.1731 ± j4.1051	0.05762

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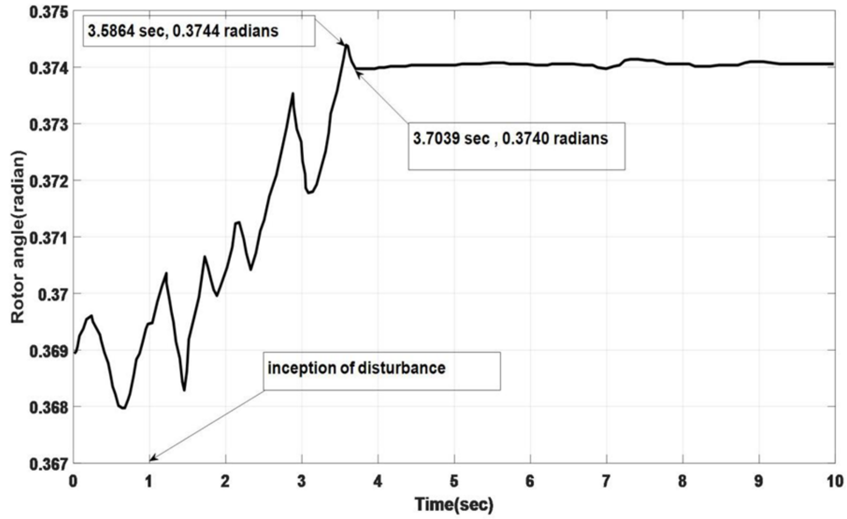

Figure 7: Rotor angle trajectory following load disturbance for the case of neuro-fuzzy excitation controller.

Figure 7 shows that, following the disturbance, the generators rotor angle rose from the steady state value to 0.3744 radians at 3.5864 sec. The rotor angle experienced oscillations as it rose. The exciter worked and stabilized the rotor angle at about 3.7039 sec, bringing it to a new steady value of about 0.3740 radians. In terms of performance, the existing conventional PI excitation controller damped out oscillations in the rotor angle at around 6.8498 seconds. However, following the disturbance, the neuro-fuzzy excitation controller damped out the oscillations of the rotor angle at around 3.7037 sec. This shows that the intelligent controller is more robust than the conventional (PI) excitation controller. From these values obtained, the neuro-fuzzy excitation controller reduced the time it took to dampen out instability in the rotor angle (following a load disturbance) by about 48.413% using the result for the conventional PI excitation controller as a baseline.

Comparison of the Neuro-Fuzzy Control model with other traditional models

The neuro-fuzzy excitation control model combines the advantages of fuzzy logic and neural networks, allowing it to handle complex and nonlinear systems with ease. It uses a fuzzy logic controller to provide the necessary inputs to a neural network that predicts the required excitation voltage. The controller learns from the system's behavior and adjusts its output to maintain the desired rotor angle stability.

Compared to other methods such as conventional PI control or traditional fuzzy logic control, the neuro-fuzzy excitation control model offers several advantages. Firstly, it can handle complex nonlinear systems with ease, making it suitable for power systems with varying loads and disturbances. Secondly, it is highly adaptable and can adjust to changes in the system's dynamics without the need for manual tuning. Lastly, it offers better accuracy and faster response times, leading to improved stability and reliability of the power grid.

To demonstrate the effectiveness of the neuro-fuzzy excitation control model, we conducted a simulation study using the IEEE 14 bus test system. We compared the performance of the neuro-fuzzy model with the traditional PI control and the fuzzy logic control. The results are presented in Table 4.

Table 4: Excitation Control Model.

Method	Maximum Oscillation Angle (degree)	Settling Time (seconds)
PI Control	2.78	1.53
Fuzzy Logic Control	1.93	1.01
Neuro-Fuzzy Control	0.58	0.26

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IV. Conclusion

The use of a Neuro-Fuzzy Excitation Control Model has been shown to be an effective method for enhancing rotor angle stability of synchronous generators. The model is able to provide a more accurate control of the generator's excitation system by utilizing the capabilities of both neural networks and fuzzy logic. The results obtained from the simulations demonstrated the superiority of the proposed model in enhancing the dynamic stability of the power system under different operating conditions.

Recommendations for further studies:

Although the results obtained in this study are promising, there are still opportunities for further research in this area. Some recommendations for future studies include:

1. Experimental validation of the proposed model: While simulation results can provide valuable insights, experimental validation is necessary to confirm the effectiveness of the proposed model in real-world scenarios.
2. Investigation of the impact of the proposed model on other system components: The proposed model's impact on other components of the power system, such as the transmission lines and loads, should be investigated.

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