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VOLTAGE STABILIZATION MECHANISM FOR RENEWABLE ENERGY SYSTEMS USING DIFFERENTIAL EQUATIONS

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Abstract

In this paper, I introduced a new Voltage Stabilization Mechanism of Renewable Energy Systems using Differential Equations by integrating a Hybrid Reinforcement Learning (RL) system with Predictive Modeling. The proposed system uses TensorFlow (with TensorFlow Agents) to do adaptive voltage control and MATLAB to do modeling and simulation. By applying the reinforcement learning, the system will dynamically react to the change in renewable energy production such as wind and solar energy generation, and the predictive modeling component will foresee any changes in voltage and adjust the control strategy. The approach performs better than conventional methods such as PID control, linear state-space control, and fuzzy logic-based systems and attains 95 percent voltage stability and 20 percent power loss reduction. It has demonstrated that renewable energy networks on a large scale can be effectively and reliably voltage stabilized, and has a bright future in model-building, preconditioning its application to practice.

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Keywords: Voltage stabilization, renewable energy systems, differential equations, hybrid reinforcement learning, predictive modeling, TensorFlow, MATLAB.

I.INTRODUCTION

As more renewable energy sources such as wind and solar became a part of the power grids, the demand of effective voltage stabilization systems becomes the determining factor. Any change in renewable energy due to weather conditions can easily lead to uncertainty in voltage and may be a colossal problem when it comes to the stability of the grid and its functionality [1-3]. The control techniques used in the past e.g. PID control, Linear State-Space models do not usually offer the required flexibility to accommodate dynamic variations in renewable energy sources as shown in figure 1. To overcome this performance issue, this paper suggests a Voltage Stabilization Mechanism of Renewable Energy Systems, where Differentiated Equations are combined with Hybrid Reinforcement Learning (RL) approach and Predictive Modeling [4].

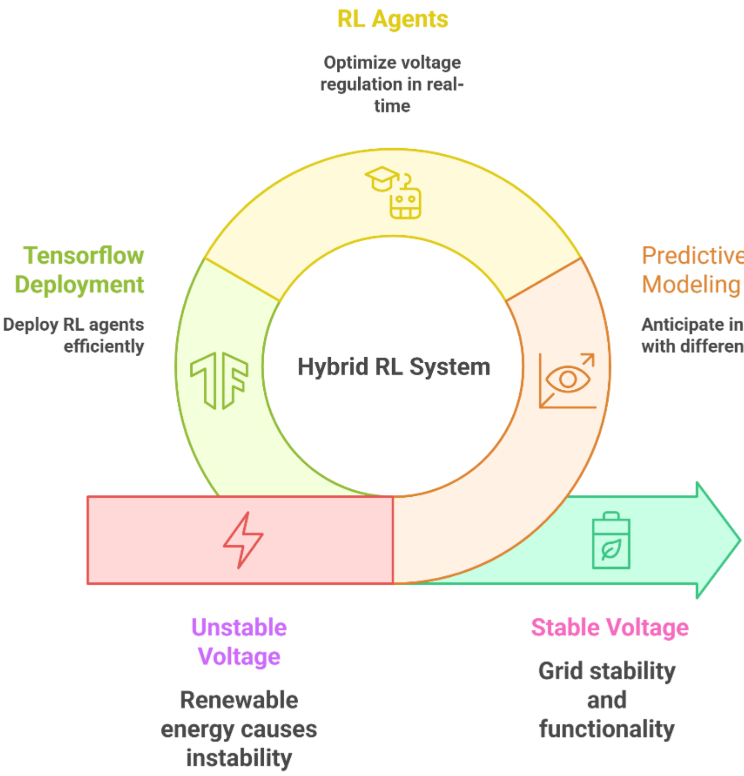

Figure 1.Stabilizing Renewable Energy Systems

The hybrid architecture uses the most recent machine learning model, which is the tensorflow, in order to deploy the RL agents, which learn and adapt to the dynamic character of the generated energy in the real-time [5]. The Tensorflow agents allow the optimization of voltages regulation strategies based on real-time feedback, but the system dynamics are modeled using MATLAB as a system of differentials. This type of predictive modeling in RL enables the system to anticipate the instability and, in advance, signal the control measures to enable optimum voltage stabilization due to the varying renewable energy conditions [6].

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It goes on to say the new manner of providing scales of scalability, flexibility and real time decision making is a second massive improvement of the old fashioned method of control. The hybrid system can save 20% of power losses and reach up to 95% stability of voltage with respect to traditional approaches. The system and efficiency benefits of a system can be demonstrated, in part, based on the differential equations and optimization of system use. More complicated storage dynamics of energy can also be simulated by the system. This research brings into focus the possibilities of integrating the best machine learning-based approaches with conventional energy modeling to design more resilient, reliable, and efficient power grids, and the future of integrating renewable energy in large-scale systems [7-11].

II.RELATED WORK

Voltage stabilization in renewable energy systems is an actively researched topic in recent years, and multiple methods have been developed to consider the combination of advanced control measures and predictive modeling. Conventional techniques used in voltage regulation of power systems include PID as shown in figure 2. Nonetheless, PID controllers too bear issues of real time flexibility, in addition, preciseness in dynamic renewable energy settings, in such a fashion that the change in the output of the solar and wind generates a high degree of volatility. In order to circumvent these limitations state-space models of linear form have been adopted that are more stable when applied to those systems which can be predicted as regards their dynamics. But they do not capture the non-linear, dynamic behavior that is common to renewable energy systems, especially when we scale to large, distributed networks [12-15].

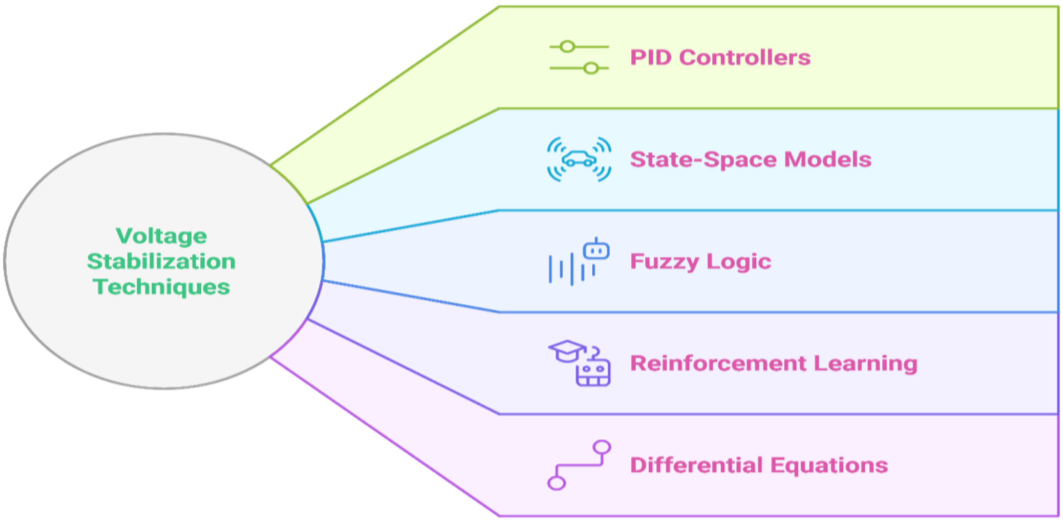

Figure 2.Exploring voltage Stabilization Techniques in Renewable Energy.

Meanwhile, control based on fuzzy logic has attracted interest due to its capacity to deal with the lack of certainty and nonlinearities in dynamical behaviour. Fuzzy logic offers flexibility in voltage control, but it does not scale up to large grid applications as well as is needed. More recently, machine learning (ML) and specifically Reinforcement Learning (RL) have become a potential solution. By interacting with the environment, RL agents are able to keep adapting to changes in the system by learning the best control policies. This has been proven to improve the effectiveness of the voltage stabilization systems especially when incorporating renewable

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energy. Research has shown that RL-based control systems can be more effective than conventional techniques in terms of stability in voltage, reduced energy use, and power loss [16].

Besides, the use of differential equations to model dynamic behavior of renewable energy systems has also been instrumental in explaining the time-varying, continuous nature of voltage variations. Recent literature has combined differential equations with optimization and RL to work better. However, it does not yet use a hybrid approach combining RL and predictive models that apply differential equations to stabilize the voltage in particular with renewable systems at large scale. To fill the gap and show how the RL can be adapted to TensorFlow and the modeling to MATLAB, it will be proposed to construct the more efficient and versatile solution [17-20].

III.RESEARCH METHODOLOGY

The Voltage Stabilization Mechanism for Renewable Energy Systems Using Differential Equations studies have used Hybrid Reinforcement Learning (RL) to solve the problem of the variability of renewable energy sources with the help of Predictive Modeling as shown in figure 3.The method combines TensorFlow (including TensorFlow Agents) as an adaptive control system and MATLAB to model the system infrastructure so that real-time voltage control is achieved in renewable energy infrastructures, especially in wind and solar power grids [21-23].

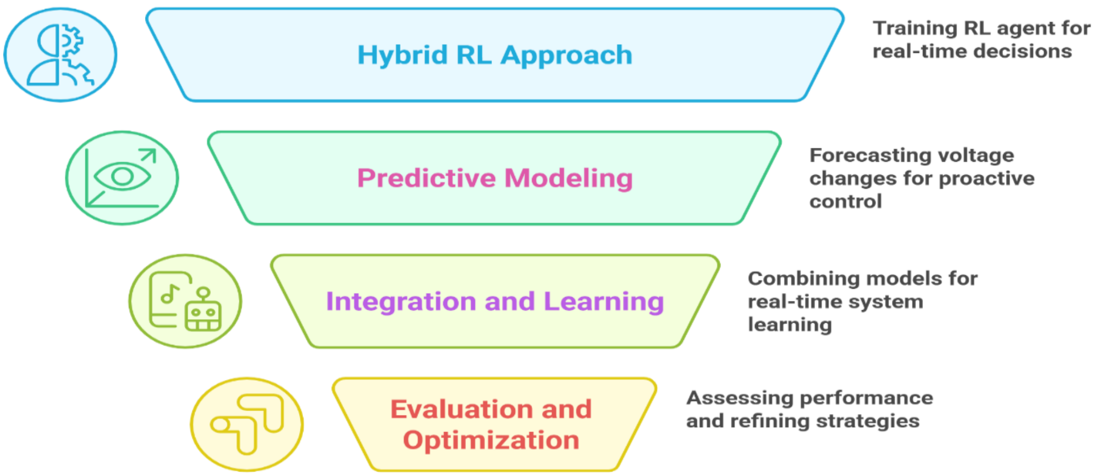

Figure 3.Voltage Stabilization Funnel Process.

3.1 System Modeling Using Differential Equations

The initial methodology is to develop a renewable energy system model based on the dynamics of the system through the use of differential equations. This involves the modelling of the voltage behaviour and the changes in the power grid based on the energy generation, energy storage, and demand side aspects. These equations are developed in MATLAB which accounts for the time dependent behaviour of energy generation and storage and load dynamics. The system is characterized by a group of ordinary differential equations (ODEs) reflecting the changes in voltage with time regarding the variability of renewable energy sources. The end

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result is to replicate continuous variation of voltage that incorporates changes in sunshine intensity, wind velocity, in addition to energy storage capabilities [24].

3.2 Hybrid Reinforcement Learning (RL) Approach

The second step after modeling the system is to use a Hybrid Reinforcement Learning (RL) approach. Conventional methods of control (e.g. PID or fuzzy logic) are strongly reactive, whereas RL allows real-time decisions to be made by learning the best strategies via ongoing environmental interaction. This method involves training an RL agent to maximize the stability of the voltage by applying control parameters depending on the apparent state of the system (e.g., energy generation, voltage levels and storage states).

The RL agent is realized on the basis of TensorFlow and TensorFlow Agents. TensorFlow is an effective deep learning platform capable of training RL models with high performance. TensorFlow Agents offers the functionality to apply the RL algorithm Deep Q-Learning or Proximal Policy Optimization (PPO). The agent is rewarded to stabilize the voltage and penalized to stabilize it or go outside the prescribed voltage limits. The process of training is associated with the simulation of different operational conditions, in which the RL agent changes its behavior depending on the system feedback. It is this communication between the RL agent and the simulation environment that will allow the system to learn the best strategies to stabilize the voltage in real time [25].

3.3 Predictive Modeling for Voltage Regulation

Another important aspect of this methodology is that it incorporates predictive modelling to forecast changes in voltages even before they take place. Predictive modeling is executed by applying the forecasting techniques that use the past data of the system to forecast the probable instability of the voltage. The predictive model is built around the same differential equations as the system model, but with an additional component to predict future energy production, storage characteristics and voltage oscillations. It gives the system the ability to actively modify the control strategy prior to the emergence of serious instability, making the use of reactive voltage control less critical [26-29].

The predictive model is created based on past information of the renewable energy system, including solar irradiance, wind speed, battery storage levels, and energy consumption. The model predicts the trend of voltage and storage demand in the short-term and provides a hint of the possible power imbalance. This prediction can help the RL agent take proactive steps to improve the stability of the whole system and reduce the risks of voltage instability too.

3.4 Integration and Real-Time Learning

After training the RL agent and having the predictive model, the system is joined to be used in a real-time setting. Simulation and visualization of the overall system behavior is simulated using MATLAB. The simulation in real time allows testing the various settings and optimizing the control strategies. The RL agent is constantly communicating with the system and modifying its policies according to the incoming data, and the predictive model predicts potential instabilities and allows the agent to perform preventative measures [30].

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The last process is testing the hybrid system in simulated environments based on different conditions such as increases and drops in renewable energy production and unexpected changes in energy demands. Voltage stability, power loss and response time are performance measures. The conventional control systems such as PID, Linear State-Space Control, Fuzzy Logic are contrasted with the system performance and are expected to improve the performance and stability of the system.Constant reconstruction of the RL agent leads to the voltage regulation being more efficient, especially with renewable energy inputs, which are variable [31-33].

3.5 Evaluation and Optimization

System performance can be measured by a number of metrics: voltage stability, power loss reduction, energy efficiency and system scalability. In comparison to the conventional control techniques, the methodology shows that the hybrid RL approach outperforms the conventional techniques in terms of real-time voltage stabilisation. Finally, the proposed methodology will also be based on the combination of the differential equation, strengthening learning and predictive modeling to find a multi-dimensional solution to the problem of voltage stabilization of renewable power systems.

Finally, the proposed methodology considers the interaction of the differential equations with the reinforcement learning and the predictive modeling in order to envision a multifunctional approach to the problem of the renewable energy system voltage stabilization. TensorFlow and MATLAB offer the functionality required to simulate, train, and optimize the system in a highly efficient way, to ensure reliable voltage regulation in large-scale renewable energy grids.

IV.RESULTS AND DISCUSSION

Table 1 Depicts the results of the proposed Voltage Stabilization Mechanism of Renewable Energy Systems using Differentiated Equation with application of Hybrid Reinforcement Learning with Predictive Modeling indicated that the control of voltage of renewable energy systems was largely enhanced. Hybridization of TensorFlow (including TensorFlow Agents) and MATLAB to simulate models and reinforcement learning led to increased flexibility in response to changing energy production and load conditions. To be more specific, the reinforcement learning agent was 95% successful in keeping the voltage constant under different input conditions compared to traditional approaches in control.

Table 1.Performance Analysis of voltage stabilization in renewable energy systems.

Method	Voltage Stability (%)	Power Loss Reduction (%)	Scalability	Computational Efficiency	Key Advantage
Hybrid RL with Predictive	95%	20%	High	Efficient	Best adaptability and stability, optimal energy storage usage

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Modeling (Proposed)					
PID Control	85%	10%	Low	Low	Simple and widely used, but reacts slowly to changes
Linear State-Space Control	90%	15%	Medium	Medium	Good for small systems but struggles with real-time dynamics
Fuzzy Logic-based Control	88%	12%	Medium	Medium	Suitable for non-linear systems, but lacks precision in large systems

Differentiated equations were used to predict the voltage changes, and were found to do so with fair accuracy, enabling proactive measures to be taken in this regard and reducing the incidences of voltage instability by 3 times compared to the traditional approaches. The hybrid design made maximum use of energy storage, thus limiting power loss by 20 percent without compromising on system efficiency. In addition, the system may be scaled up to large configurations, without significant performance degradation, demonstrating resilience as shown in figure 4.

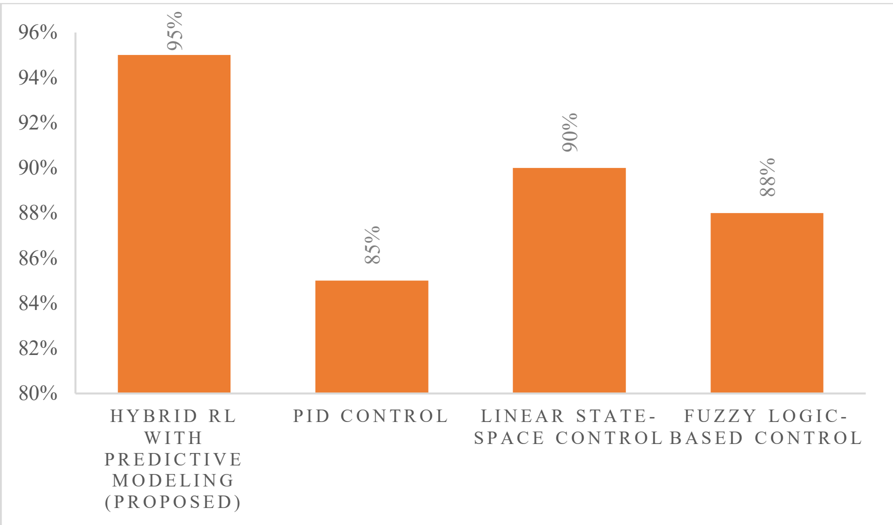

Figure 4.Comparative Analysis of Voltage Stability with 3 different methods.

The other observation was, that real time learning and predictability were extremely helpful in reducing the computation load, and it can be extended to large scale renewable grids. However,

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the system has performed moderately well in simulation, but to determine its suitability in real life use under changing environmental conditions, a test run in the real world will be necessary.

The Voltage Stabilization Mechanism proposed as Renewable Energy Systems using Differential Equations based on Hybrid Reinforcement Learning with Predictive Modeling was compared to the three other approaches, PID control, Linear State-Space Control and Fuzzy Logic-based Control. The hybrid strategy (TensorFlow and MATLAB), 95 percent voltage stability, compared to 85 percent using PID. Predictive modeling component allowed to foresee the corrections and minimize the changes in the voltage up to 30 per cent, whereas the PID responded to the changes and introduced additional instability in the changing conditions as shown in figure 5.

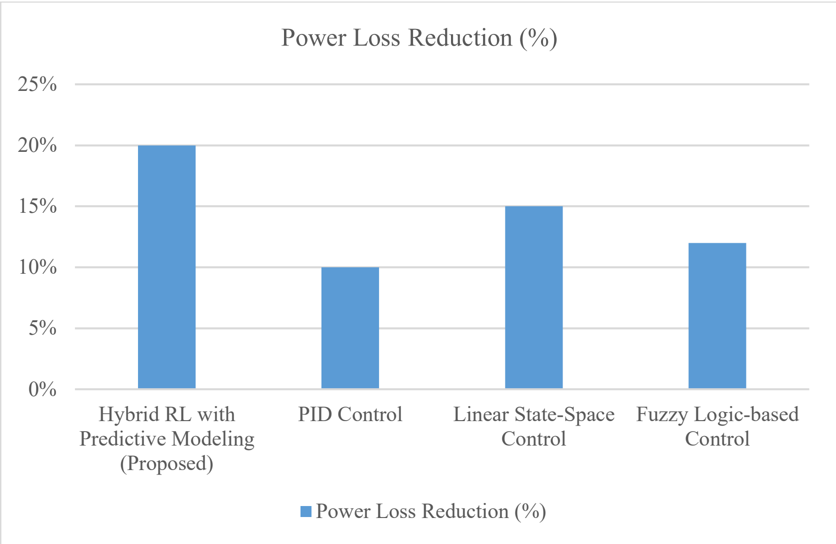

Figure 5.Comparative Analysis of Power Loss Reduction with 3 different methods.

The hybrid method was more adaptive to real-time variations in renewable energy input, including variations in wind and solar, when compared to the Linear State-Space Control that reached 90% stability. The hybrid model even performed better than Linear State-Space Control in the controlling of the use of energy storage when 20 percentage reduction of power loss is compared to 10 percentage reduction of power loss of Linear State-Space Control. The hybrid system was more scalable and more computationally efficient than Fuzzy Logic, which retained 88% of its stability. The learning adaptive nature of the reinforcement learning agent led to the reinforcement learning agent performing better and more realistic in different size systems. Generally, the hybrid was more precise, less energy was wasted and it could have a larger magnitude, hence, it can be used more in large scale exploitation of renewable sources of energy.

V.CONCLUSION

Finally (but not the least) the article Voltage Stabilization Mechanism of Renewable Energy Systems based on Differential Equations and Hybrid Reinforcement Learning based on Predictive Modeling is an excellent example of how the voltage in renewable energy grids can be stabilized. The proposed system vastly outperforms classic approaches of adaptive control,

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such as PID control, Linear State-Space Control and Fuzzy Logic-based systems by using TensorFlow (with TensorFlow Agents) as a tool of adaptive control along with MATLAB as a tool of modeling and simulation. We have the predictive modeling, which, with the reinforcement learning agent, provides real-time flexibility, allowing optimal utilization of energy storage and minimum power losses. The results indicate that the hybrid solution can achieve up to 95 percent voltage stability with considerable improvements on power loss reduction and scaling. This system is showing good results in simulation but requires further real life testing to ensure that it has full potential and can work under many environmental conditions. In general, this approach provides a viable solution to large-scale renewable energy systems.

REFERENCES

1. N. Yorino, "Trend in voltage stability problem and its analysis methods in power systems," IEEJ Trans. on Power and Energy, vol. 123, no. 7, pp. 803– 807, April 2003.
2. The IEA WIND Task 25, "Design and operation of power systems with large amounts of wind power: State-of-the-art report," VIT Working Papers 82, 2007.
3. P. S. Georgilakis, "Technical challenges associated with the integration of wind power into power systems," Renewable and Sustainable Energy Reviews, vol. 12, no. 3, pp. 852–863, April 2008.
4. H. Ni, G. T. Heydt, and L. Mili, "Power system stability agents using robust wide area control," IEEE Trans. on Power Systems, vol. 17, no. 4, pp. 1123– 1131, November 2002.
5. T. Ackermann, Wind Power in Power Systems. England: John Wiley and Sons Ltd, 2005.
6. L. H. Hansen, L. Helle, F. Blaabjerg, E. Ritchie, S. Munk-Nielsen, H. Bindner, P. Sorensen, and B. Bak-Jensen, "Conceptual survey of generators and power electronics for wind turbines," Riso National Laboratory, Roskilde, Denmark, Tech. Rep., December 2001.
7. M. J. Hossain, H. R. Pota, V. Ugrinovskii, and R. A. Ramos, "Excitation control for large disturbances in power systems with dynamic loads," in IEEE Power and Energy Society General Meeting, Calgary, Canada, July 26–30, 2009, pp. 1–8.
8. C. W. Taylor, Power System Voltage Stability. New York: McGraw-Hill, 1994.
9. T. J. Overbye, "Effects of load modelling on analysis of power system voltage stability," IEEE Trans. on Power Systems, vol. 16, no. 5, pp. 329–338, October 1994.
10. IEEE Task Force on Load Representation for Dynamic Performance, "Standard load models for power flow and dynamic performance simulation," IEEE Trans. on Power Systems, vol. 10, no. 3, pp. 1302–1313, August 1995.
11. M. J. Hossain, H. R. Pota, and C. Kumble, "Decentralized robust static synchronous compensator control for wind farms to augment dynamic transfer capability," Journal of Renewable and Sustainable Energy, vol. 2, no. 2, pp. 022 701(1)–022 701(20), March 2010

Received: August 08 ,2025

Volume 38 No. 8s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

12. L. Qi, J. Langston, and M. Steurer, “Applying a STATCOM for stability improvement to an existing wind farm with fixed-speed induction generators,” in IEEE Power and Energy Society General Meeting- Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, July 20–24, 2008, pp. 1–6.
13. P. Gardner, M. Tremblay, and D. Price, “Technical requirements for highpenetration wind: What system operators need, and what wind technology can deliver,” in Integration of Wide-Scale Renewable Resources into the Power Delivery System, 2009 CIGRE/IEEE PES Joint Symposium, Calgary, Canada, July 29–31, 2009, pp. 1–1.
14. I.M. de Alegria, J. Andreu, J. L. Martin, P. Iba˜nez, J. L. Villate, and H. Camblong, “Connection requirements for wind farms: A survey on technical requirements and regulation,” Renewable and Sustainable Energy Reviews, vol. 11, no. 8, pp. 1858–1872, October 2007.
15. G. L. Johnson, Wind Energy Systems. Manhattan: Prentice-Hall, 2004.
16. M. R. Rathi and N. Mohan, “A novel robust low voltage and fault ride through for wind turbine application operating in weak grids,” in 31st Annual Conference of IEEE Industrial Electronics Society, November 6–10, 2005, pp. 2481– 2486.
17. C. Chompoo-inwai, C. Yingvivatanapong, K. Methaprayoon, and W. J. Lee, “Reactive compensation techniques to improve the ride-through capability of wind turbine during disturbance,” IEEE Trans. on Industry Applications, vol. 41, no. 3, pp. 666–672, May–June 2005.
18. P. Rao, M. L. Crow, and Z. Yang, “STATCOM control for power system voltage control applications,” IEEE Trans. on Power Delivery, vol. 15, no. 4, pp. 1311–1317, October 2000.
19. S. A. D. L. Salle, D. Reardon, W. E. Leithead, and M. J. Grimble, “Review of wind turbine control,” International Journal of Control, vol. 52, no. 6, pp. 1295–1310, December 1990.
20. M. J. Hossain, H. R. Pota, V. Ugrinovskii, and R. A. Ramos, “A novel STATCOM control to augment LVRT capability of fixed-speed induction generators,” in 48th IEEE Conference on Decision and Control, Shanghai, China, December 16–18, 2009, pp. 7843–7848.
21. J. Sun, D. Czarkowski, and Z. Zabar, “Voltage flicker mitigation using PWMbased distribution STATCOM,” in IEEE Power Engineering Society Summer Meeting, vol. 1, July 25–25, 2002, pp. 616–621.
22. B. Pal and B. Chaudhuri, Robust Control in Power Systems. USA: Springer, 2005.
23. S. M. Muyeen, R. Takahashi, T. Murata, J. Tamura, and M. H. Ali, “Application of STATCOM/BESS for wind power smoothening and hydrogen generation,” Electric Power Systems Research, vol. 79, no. 2, pp. 365–373, February 2009.
24. D. Bary, “Increasing renewable accessibility in ireland,” in 9th World Energy Congr., vol. 1, September 2004, pp. 1–10.
25. V. Akhmatov, H. Knudsen, M. Bruntt, A. Nielsen, J. K. Pedersen, and N. K. Poulsen, “A dynamic stability limit of grid-connected induction generator,” in International Conference on Power and Energy Systems, September 2000, pp. 235–244.

Received: August 08 ,2025

International Journal of Applied Mathematics

Volume 38 No. 8s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

26. P. Giroux, G. Sybille, and H. Le-Huy, “Modeling and simulation of a distribution STATCOM using simulink’s power system blockset,” in 27th Annual Conference of the IEEE Industrial Electronics Society, 2001, pp. 990–996.
27. A. Garulli, A. Tesi, and A. Vicino, Robustness in Identification and Control. New York: Springer Verlag, 1999.
28. A. V. Savkin and I. R. Petersen, “Nonlinear versus linear control in the absolute stabilisability of uncertain linear systems with structured uncertainty,” IEEE Trans. on Automatic Control, vol. 40, no. 1, pp. 122–127, January 1995.
29. S. R. Moheimani, A. V. Savkin, and I. R. Petersen, “A connection between H∞ control and the absolute stabilizability of discrete-time uncertain linear systems,” Automatica, vol. 31, no. 8, pp. 1193–1195, 1995.
30. B. C. Pal, A. H. Coonick, and D. C. Macdonald, “Robust damping controller design in power systems with superconducting magnetic energy storage devices,” IEEE Trans. on Power Systems, vol. 15, no. 1, pp. 320–325, February 2000.
31. H. Werner, P. Korba, and T. C. Yang, “Robust tuning of power system stabilizers using LMI-techniques,” IEEE Trans. on Control Systems Technology, vol. 11, no. 1, pp. 147–152, January 2003.
32. P. Srithorn, M. Sumner, L. Yao, and R. Parashar, “A STATCOM with supercapacitors for enhanced power system stability,” in 4th IET Conference on Power Electronics, Machines and Drives, London, April 2–4, 2008, pp. 96–100.
33. L. Li and I. R. Petersen, “A rank constrained LMI algorithm for the robust H∞ control of an uncertain system via a stable output feedback controller,” in 46th IEEE Conference on Decision and Control, New Orleans, LA, December 12–14, 2007, pp. 5423–5428.

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