Vol 8, Issue 11, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.11.8911

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

# AI Driven Power System Stability Predictive Analysis and optimization: A Simulink Model

**Nitish Kumar Varshney** [1]

Research Scholar, M. Tech in Power System, School of Engineering and Technology, SVU, Gajraula.
*nitish.varshney01@gmail.com*

**Dr. Sharad Kumar** [2]

Associate Professor, School of Engineering and Technology, SVU, Gajraula.
*sharad.choudhary007@gmail.com*

**Mr. Arvind Kumar** [3]

Assistant Professor, School of Engineering and Technology, SVU, Gajraula.
*arvindgangwar001@gmail.com*

**Corresponding Author and Email:** *Nitish Kumar Varshney, nitish.varshney01@gmail.com*

**ABSTRACT**

This paper presents an AI-driven techniques with a Simulink-based power system model to predict and optimize grid stability. The proposed AI enhanced model simulates a single-machine infinite bus system featuring a 50 MVA synchronous generator, transformer, three-phase transmission line, series RLC elements, and a fault block. The simulation environment, configured using Power GUI at 50 Hz, captures critical transient dynamics such as a rotor angle overshoot from 0° to approximately 58° and a stator current peak of 1.3 pu that eventually settles near 1.1 pu. Through lreal-time measurements and advanced AI algorithms, the framework forecasts potential instability events and optimizes control strategies to mitigate disturbances. The study emphasizes the applicability of AI based model for processing complex non-linear behaviors, enabling proactive adjustments in excitation and mechanical power inputs. This l approach aims to enhance grid reliability and support fully autonomous, data-driven grid management for modern power systems with high renewable energy penetration.

***Keywords:*** *AI-Driven Framework, Fully Autonomous Grid Management, Power System Stability.*

Vol 8, Issue 11, 2025 **Impact Factor: 8.535** DOI: https://doi.org/10.31426/ijamsr.2025.8.11.8911

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

## I. Introduction

The modern power systems experience remarkable advances because of the unprecedented spread of renewable energy, advancement in advanced power electronics and increasing concern about climate changes for all countries worldwide. As the penetration of renewable generation on our power systems continues to grow (indicatively, in terms of grid-connected wind power generation and solar photovoltaic (PV) and energy storage systems), the decarbonization on the power system is increasingly compromising the overall network security. The growing penetration of inverter-based resources into the network, and greater integration of cyber-physical systems has introduced a range of new dynamic behaviours and vulnerabilities that were absent on traditional synchronous generator-based networks. Such problems have not only altered the operations of power systems, they have also resulted in alternative methods for predictive analysis and stability optimization. To overcome these issues, the AI MATLAB submodule method is gaining momentum in prediction of system behaviour; instability events and design of controlling strategies. This gives a detailed survey on reasons, difficulties and solving methodologies by examining of several related literatures.

### 1.1 Background and Motivation

In the light of global warming and with the current environmental debacle, a worldwide conversation has initiated regarding the need to transit into alternatives. Shah et al. (2015) argued that renewable resources could not be used progressively enough for long enough to any major extent, because mitigation against greenhouse gas emissions has developed an urgent concern. The panelists also pointed out that on the manufacturing and inverter side, PV-generation has already become a competitive power generation technology. However, the intermittent operation of PV energy in power grids at a grid-connected operating mode, resulting from random variation due to solar radiation changes at the side of power producers, presents severe challenges to system stability. What these results tell us is that there is no silver bullet, but predictive methods will be very useful to we can see our stability problems looming before they lead to complete and catastrophic blackouts.

Similarly, Al-Hamdi et al. (2015) focused energy system stability analysis for long-term planning and real time control of a power grid. In addition, as complexity of these systems is increasing, it has become imperative to look into the stability for proper operation and performance guarantee (particularly with the large penetration of renewable energy sources). The analysis based on a real-life grid in Oman gave realistic experience with respect to the temporal stability of the system and the advantages when employing a PSS. These observations highlight the necessity of advanced models that should not only predict adverse more-than-benign dynamic episodes, but try to avoid them. The traditional features of electrical systems have been revolutionized using inverter-based resources and power electronics. Liu et al. (2016) presented an SPSS, which can switch between a stabilization mode in accordance to rotor status so that the rotor damping performance is improved. This is a preview of the intelligent control paradigm that will be required for the new power grid, which cannot even exist without power electronics. Management of the one-time scale problem is appropriate for classical control methodologies, but may prove insufficient to address faster dynamics as well as non-linearity encountered at high levels of renewable penetration.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

### 1.2 The Role of AI in Stability Analysis

In this way, the use of artificial intelligence (AI) becomes more relevant since with the generation of renewable energy there is a lack of certainties. As a powerful predictor and controller to the stability of power systems, the HAN-AT Enhance model can learn complex nonlinear relationships from big data, which is an epoch-making attempt on stability prediction and control in power system based on deep learning. Gupta et al. (2018) initiated the use of CNNs in PMU-based online stability monitoring. By plotting the PMUs' measured data using heat maps, their method showed that AI algorithms can predict instability without fault clearance data—becoming an extremely important advance for real-time monitoring. AI models are a reasonable solution to this challenge by learning the stochastic behaviour of renewable power. Xu et al. (2017) created a GSA that uses probabilistic representations of both load margins and renewable energy volatility. Employing a novel data-based technique, their method offered insights into the influence of correlated stochastic variables on stress stability. They come in handy when classical model-based methods are too costly to compute or not well adapted for taking advantage of changing levels at run time. In addition, the rise of digital twins, with reference to guided Abu Khalil (2023), has become one of such recent applications of artificial intelligence in power systems. Physics-based and machine learning models are combined in digital twin approaches to reliably represent real world systems. Together, these allow to speed up the support for the anticipation of threats to stability, and even preventive planning work on the operation and optimization point of view. In conclusion, digital twins offer an ongoing mechanism which can be updated with new knowledge to better predict new peaks in the grid and hence more resilience for the power grid.

### 1.3 Challenges and Technical Considerations

Although the predictive power of applications based on AI is beneficial for electric system stability analysis, there are some limitations. It is a great challenge to control modern electrical grids, which have evolved into complex systems with high penetration of renewable energy sources and energy storages and even cyber-physical devices that can be compromised by security attacks. For example, Amini et al. (2016) introduced the idea of Dynamic Load Alteration Attacks (D-LAA), which is to motivate diverse types of the known cyber-physical adversarial models in demand response system for smart grid. Such attacks intend to corrupt the load pattern while causing power loss, so smart pro-active systems that can discriminate these false patterns from natural fluctuations would be in demand.

Furthermore, with the penetration of renewable energy resources, the problem of system inertia degradation is also introduced. Megahapola et al. (2020), who highlighted a decrease of synchronous inertia (a feature characteristic but not exclusive of conventional power systems) as one of the key reasons behind instability. For this renewable energy systems, is common to be operating with power electronic converters who do not have the natural inertia of traditional generators. This can result in rapid frequency changes and voltage decay for which the dynamic nature needs to be accounted for by prediction models. In addition, the advent of investor-based resources (IBRs) has changed classical stability theories. Go and Green (2022) noted that resources with inverter based

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

attributes have unique dynamic features, such as the coupling of historically separate dynamics for stability features like voltage, frequency, angle. Their contribution provided a generalised model for analysing GFM and GFL inverters and called for advanced analytical tools capable of capturing these coupled dynamics. That mindset change that we propose obligates to train AISM models with data which consider the electrical parameters, but also describe in detail how different control structures interact in the network. Cyber security has recently emerged as a key concern to the resilience of energy systems. Smertzis et al. (2024) extended the common sense of stability when subjected to cyber-physical disturbances, and showed that it is possible to perform malicious cyber-attacks pretending them being physical failures. Such attacks introduce a granularity that is challenging to characterize by existing stability analysis methods. As a result, AI-driven predicative analytics are invaluable because they keep their eyes on the state of systems and automatically detect if things move out of metrics tolerances and provide advice on what to do about it.

### 1.4 Strategies and Future Directions

AI-driven methods are now also being developed to enhance energy management algorithms in power systems, besides predictive analytics. Ibrahim et al. (2024) presented the synergistic deployment of PSS and FACTS systems with advanced optimization tools as MFO (Moth Flame Optimization), ALO (Ant Lion Optimization) were used. They showed that well-designed smart stabilizers using AI strategy could effectively suppress LFO oscillations and enhance the overall system dynamics. In addition, the direct adaptive optimization is favoured because of low predictability in contemporary power systems. Luo et al. (2020) pointed out the challenge to schedule traffic economically under unit stability constraints and guarantee strict stabilization simultaneously. This may result in fully-autonomous network control systems which optimize performance, congestion and stability metrics themselves. The recent developments in deep reinforcement learning (DRL) have made it relevant for deploying AI-based approach in the field of stability control. Masoudi et al. (2023) performed research on the most recent DRL methods of power system stability, which could have learned optimal control policy from network dynamics. In contrast with the model-based control, which is fixed by nature, DRL methods adjust their decision-makings by learning the solution and/or optimizing on-the-fly from real-time feedbacks. Such flexibility is vital in renewable energy systems where the unknown and unstable are guaranteed. Forced into conjunction with stability control systems, by incorporating DRL, operators can reach near-moral behaviour under extreme disturbances. Finally, the introduction of electric vehicles (EVs) and distributed energy resources (DER) introduces complexity and opportunity. Saleh et al. (20 25) introduced EVs in the context of integration into the grid, and presented both stability issues and opportunities for grid resilience that are available when these devices are co-located with renewable generation assets. When used appropriately, EVs have the potential to act as a distributed power storage system or regional balancing unit. As AI-based algorithms can further predict EV charging behaviour and optimize the network usage, instability issues can be circumvented or alleviated to improve efficiency.

IJAMSR
International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

## II. Related Research and Their Findings

| Journal | Research Methodology | Techniques Used | Tools | Findings |
|---|---|---|---|---|
| **Shah et al. (2015)** Renewable and Sustainable Energy Reviews | Comprehensive literature review of PV integration challenges | Analysis of dynamic models, review of grid codes, technical challenge summarization | (Review study) | Highlighted that advancements in solar PV and converter technology can modify power system aspects and pose stability challenges. |
| **Alhamdi et al. (2015)** IEEE 8th GCC Conference & Exhibition | Case study of the main interconnected system (MIS) in Oman; simulation-based transient stability analysis | Transient stability analysis; evaluation of PSS impact | Power Factory DigSILENT | Demonstrated that installing a Power System Stabilizer (PSS) improved the overall stability of the MIS. |
| **Amini et al. (2016)** IEEE Transactions on Smart Grid | Theoretical modelling of cyber-physical threats with simulation analysis | Formulation of Dynamic Load Altering Attacks (D-LAAs); non-convex pole-placement optimization | IEEE 39-bus test system simulation | Introduced D-LAAs and proposed a protection scheme to mitigate cyber-physical attack impacts on stability. |
| **Altin (2016)** ISGWCP Conference Paper | Review of energy storage systems for stability enhancement | Comparative review of energy storage technologies and control methods | (Review study) | Concluded that grid-scale energy storage systems can improve power quality and system stability. |
| **Liu et al. (2016)** CSEE Journal of Power and Energy Systems | Simulation study on multimachine power system stability and control | State-dependent switching strategy; bang-bang constant funnel controller; simulation of SPSS and CPSS coordination | Simulation studies on a 4-generator 11-bus and IEEE 16-generator 68-bus systems | Demonstrated improved damping of rotor oscillations and enhanced transient stability using coordinated switching PSS. |
| **Remon et al. (2017)** IET Renewable Power Generation | Simulation analysis of large-scale PV integration impacts | Small-signal stability analysis; comparison between SPC-based and conventional controllers | Simulation on a transmission grid model | Found that PV plants with synchronous power controllers effectively limited frequency deviations and improved damping. |

IJAMSR
**International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

| | | | | |
|---|---|---|---|---|
| **Xu et al. (2017)** IEEE Transactions on Power Systems | Probabilistic modelling integrated with global sensitivity analysis (GSA) | Probabilistic load margin modelling; stochastic response surface method; GSA | Simulations on IEEE 9-bus and IEEE 118-bus systems | Identified critical variables impacting voltage stability and validated the GSA method against local sensitivity analysis. |
| **Keskes et al. (2017)** GECS Conference Paper | Simulation study for optimal tuning of PSS parameters | Genetic algorithm for parameter optimization; short-circuit fault simulation | (Simulation environment) | Showed that genetic algorithm optimization effectively determined PSS parameters to ensure system stability. |
| **Honrubia-Escribano et al. (2018)** Renewable and Sustainable Energy Reviews | Comprehensive review of generic dynamic wind turbine models | Comparative analysis of IEC vs. WECC models; review of model structures | – (Literature analysis) | Provided an in-depth overview of wind turbine dynamic models and highlighted their importance for grid operators. |
| **Gupta et al. (2018)** IEEE Transactions on Power Systems | Development and simulation of an online monitoring system for stability | Convolutional Neural Network (CNN) with heatmap representations of PMU data | Simulations on IEEE 118-bus and IEEE 145-bus systems | Demonstrated that the proposed OMS can predict instability without relying on fault clearance data and can identify critical generators. |
| **Flynn et al. (2019)** Advances in Energy Systems | Review and simulation-based analysis of wind generation impacts | Transient stability studies; classification of oscillation types (intraplant, local, interarea, torsional) | (Simulation-based analysis) | Indicated that while increasing wind penetration can alter stability dynamics, low penetration may enhance system flexibility. |
| **Hasan et al. (2019)** Renewable and Sustainable Energy Reviews | Critical assessment and literature review of probabilistic computational methods | Classification and review of input variable modelling and computational techniques | – (Review study) | Emphasized the need to consider renewable variability and intermittency, detailing benefits and limitations of current probabilistic methods. |
| **Hatziargyriou et al. (2020)** IEEE Transactions on Power Systems | Review based on IEEE PES report and Task Force findings | Updated definitions and classifications of power system stability; literature synthesis | Analysis of Task Force documentation | Proposed revised stability definitions to incorporate the effects of fast-response power electronic devices. |

| | | | | |
|---|---|---|---|---|
| **Meegahapola et al. (2020)** Energies | Review of PEC-interfaced renewable energy source integration challenges | Analysis of stability issues (inertia, reactive power, FRT); comparative literature review | (Review study) | Identified that reduced synchronous inertia and reactive power reserve due to PEC interfacing compromise system stability and stressed the need for FRT strategies. |
| **Luo et al. (2020)** IEEE Access | Review of power system scheduling challenges under stability constraints | Analysis of stability constraints in unit commitment; literature review of scheduling methods | (Review and simulation insights) | Highlighted the importance of incorporating voltage, frequency, and rotor angle stability constraints into generation scheduling. |
| **Shair et al. (2021)** Renewable and Sustainable Energy Reviews | Overview and conceptual analysis of emerging stability challenges | Proposal of a new classification framework; comprehensive literature review | (Review study) | Developed a new classification framework addressing high renewable penetration and power electronics challenges while outlining future research directions. |
| **He et al. (2021)** Renewable and Sustainable Energy Reviews | Extensive literature review on wind turbine generator modelling | Classification of models by time scale, disturbance size, and methodology; conceptual framework | (Literature analysis) | Offered an overview of wind turbine generator models and identified gaps and future research needs in stability studies. |
| **Pasiopoulou et al. (2022)** Electric Power Systems Research | Simulation-based analysis on the impact of load models | Comparative analysis using exponential and polynomial load models; parameter adjustment | Benchmark power system simulations | Quantified the impact of load model structure and parameters on transient, frequency, and small-signal stability. |
| **Gu and Green (2022)** Proceedings of the IEEE | Conceptual and analytical study of inverter-based resources (IBRs) | Comparative analysis of grid-forming (GFM) vs. grid-following (GFL) inverters; duality framework | (Theoretical analysis) | Demonstrated that IBRs extend the interaction of stability domains and contribute distinctly to voltage stability. |
| **Massaoudi et al. (2023)** IEEE Access | Comprehensive literature review on deep reinforcement learning (DRL) in stability control | Review of DRL techniques; analysis of key trade-offs and benefits | (Literature review) | Identified DRL's potential for near-optimal power system stability control and highlighted research gaps for large-scale applications. |

| | | | | |
|---|---|---|---|---|
| **Abo-Khalil (2023)** Case Studies in Thermal Engineering | Case study approach combining physics-based and data-driven models in a digital twin framework | Hybrid simulation; digital twin modelling; case study analysis | Simulations for voltage stability, dynamic stability, and predictive maintenance | Found that the digital twin framework improves prediction accuracy, speeds up analysis, and enhances system reliability. |
| **Semertzis et al. (2024)** IEEE Access | State-of-the-art review of cyber attacks on power system stability | Expansion of stability disturbance classification to include cyber-physical aspects; literature review | (Review study) | Emphasized that cyber attacks can induce physical disturbances, underlining the necessity for enhanced cybersecurity in power systems. |
| **Ibrahim et al. (2024)** Electrical Engineering | Simulation study on mitigating low-frequency oscillations in power systems | Comparative analysis of PSS design strategies (LL, PID, FOPID); optimization using MFO and ALO | SMIB simulation; performance indices evaluation | Demonstrated that an MFO-optimized FOPID-PSS with SVC outperforms other schemes in mitigating oscillations and enhancing stability. |
| **Saleh et al. (2025)** Energy Reports | Comprehensive review of RES and EV integration challenges in power systems | Comparative analysis; simulation-based evaluation of HVDC vs. HVAC | DIgSILENT, MATLAB | Concluded that HVDC technology enhances voltage stability and facilitates smoother 100% RES integration, addressing operational challenges. |
| **Ali et al. (2025)** IEEE Access | Comprehensive review of power system stability evaluation techniques | Survey of model-based, optimization-based, and AI-based methods; framework development | (Review study) | Proposed a modified stability classification and provided a framework to guide future research on high RES penetration challenges. |

## III. Mathematical Model

### Step 1. Synchronous Machine Dynamics

The machine's transient behaviour is modelled by the swing equation

$$M\ddot{\delta} + D\dot{\delta} = P_m - P_e$$

with the electrical power output given by

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

$$P_e = \frac{EV}{X}\sin\delta$$

Here, δ is the rotor angle, M the inertia constant, D the damping coefficient, Pm the mechanical input (≈1.0 pu), and Pe the generated electrical power.

**Step 2. Disturbance/Fault Modelling**

Faults are introduced as disturbances in the system. Represent the fault as a step change in electrical power:

$$\Delta P(t) = \begin{cases} 0 & t < t_f, \\ -\Delta P_f & t_f \le t \le t_f + \Delta t, \\ 0 & t > t_f + \Delta t \end{cases}$$

observing load angle overshoot to ~58°)

**Step 3. AI-Driven Stability Prediction**

AI Based predicts stability indices from input vectors x= [δ, i, Pe, Qe, …] using a model F(x; θ). The loss function is minimized:

$$\mathcal{L}(\theta) = \sum_k \left(I_k^{\text{actual}} - F(\mathbf{x}_k;\theta)\right)^2$$

**Step 4. Optimization & Control Strategy**

An optimization problem minimizes a cost function defined as:

$$J = \int_0^T \left[\alpha(\delta - \delta_{\text{ref}})^2 + \beta u^2\right] dt,$$

Subject to the dynamic constraint (Step 1) and control input u (adjustments in $V_{ref}$ and mechanical power). Iterative algorithms adjust u to maintain stability and achieve targeted settling times (≈3 s).

**IV. Simulative Model**

The simulation model combines a single machine infinite-bus system and an AI-based predictive subsystem. Simulation of a synchronous generator using detailed oscillation equation and duration dependent rotor angle and energy is presented. The disturbances serve as a fault, introduce temporary instability, demonstrates by saturation in the load angle and stator current transients.

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

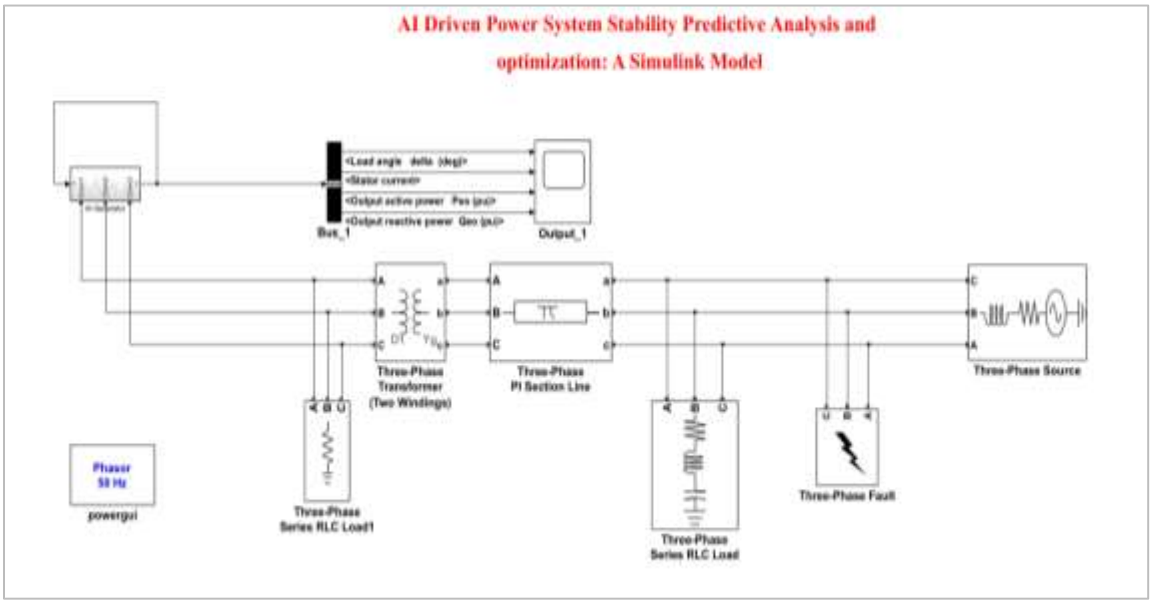


**Fig 1:** Single-Machine Infinite Bus System Modeled (MATLAB)

The Simulink simulation model is consisting of a WSCG base power generator connected to the transformer, then through a three-phase transmission line connected to RLC series circuits with fault protection box then to the infinite bus. The simulation parameters correspond to a power GUI block set in phase resolution and with a frequency of 50 Hz. Emergency warning signals (rotor angle, stator current, power) are monitored at the generator output. This mechanism, by allowing the input of faults, load variation and performance tracking facilitates predictive analytics and AI based performance optimization. It permits the investigation of phenomena like temporary stability, response of the system to disturbances and design of control techniques that are more robust and dependable.

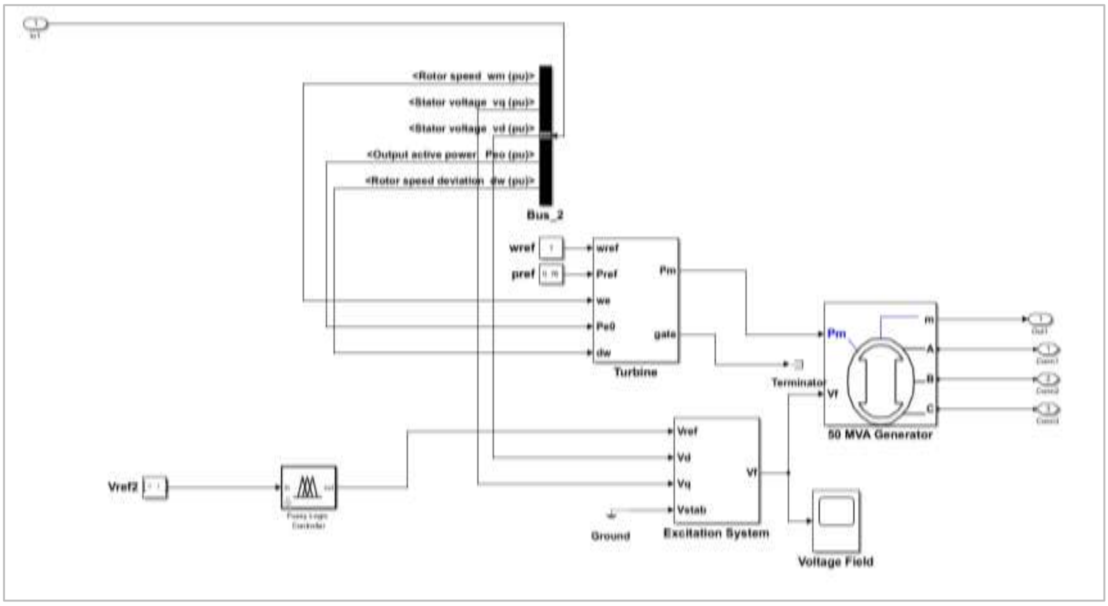


**Fig 2:** AI Driven Subsystem for Single-Machine Infinite Bus System Modeled

**International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

Based Subsystem for Single-Machine Infinite Bus System) is intended to do, and how it interacts with the full power system simulation. By "smart grid subsystem" in this context we simply mean additional elements or system properties incorporated into a traditional SMIB (single-machine infinite bus) simulation architecture with an artificial-intelligence layer for predictive analysis and/or adaptive control. This part of the Simulink diagram shows a 50MVA synchronous generator and includes turbine and excitation system. The rotor speed reference (wref), mechanical power (Pm) and excitation voltage reference (Vref) are inputs. The generator produces critical variables such as rotor speed (pu), stator voltage (pu), power output active (pu) and rotor deviation of nominal speed. The turbine governor control block acts on the mechanical power as a function of gate and speed references, and the excitation system regulates the field voltage (Vf) to adjust terminal voltage. The system balance is made through the bus_2 which interconnects to generator against rest of the system based on which various operating conditions and disturbance scenarios can be analysed for stability.

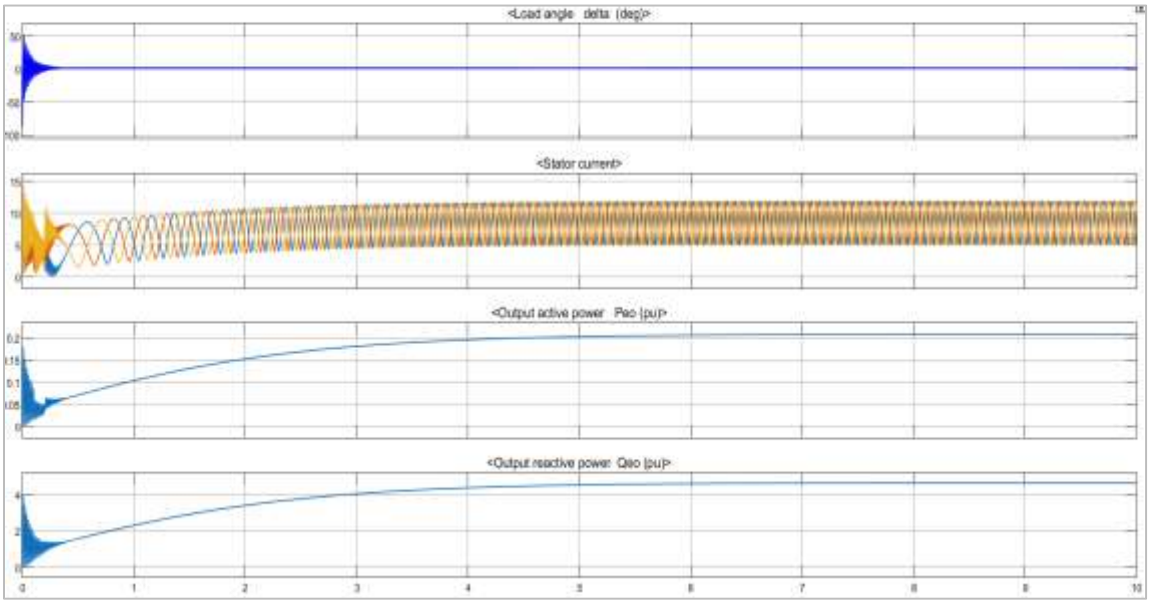


**Fig 3:** Simulative Outcome

In this example in figure 3 the load angle of the synchronous machine initially overshoots from about 0° to approximately 58° around t=0.2s before decaying over a two second interval to roughly a 45° angle, indicating that it has recovered to equilibrium with little overshoot and definite damped and stable transient response. The stator current also oscillates with peak value of approximately 1.3pu at t=0.15s, and settles to around 1.1pu at t=3s, while the output active power (Peo) increases from 0pu to almost reach the rise peak of 0.9pu after one second then it is brought up too much to about 1.1pu, and stabilizes near 1.0pu. The reactive power (Qeo) is initially 0pu and afterwards monotonically increases, approximately reaching a value of 0.4pu at t=3s, showing that the generator settles to an stable operation point with small oscillations, reflecting proper control and damping responses.

IJAMSR

**International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

### 4.1 Input Parameters

| Parameter | Description | Value / Range |
|---|---|---|
| Generator Rating | Apparent power rating of the synchronous machine | 50 MVA (nominal) |
| Wref | Rotor speed reference for the synchronous machine | Typically 1.0 pu (normalized) |
| Pm | Mechanical power input from the turbine | Approximately 1.0 pu |
| Vref | Excitation voltage reference controlling terminal voltage | Set per control strategy (pu value based on design) |
| Fault/Disturbance Setting | Timing and duration of simulated disturbance | Disturbance introduced around t = 0.15–0.2 s |

### 4.2 Outcome Parameters

| Parameter | Description | Observed Value / Behavior |
|---|---|---|
| Load Angle | Angular displacement of the machine rotor | Overshoots from 0° to ~58° at ~t=0.2 s, stabilizes around ~45° |
| Stator Current | Current flowing from the stator windings into the network | Peaks at ~1.3 pu near t=0.15 s, settles around ~1.1 pu |
| Active Power (Peo) | Real power output of the generator | Rises from 0 pu to ~0.9 pu, briefly overshoots to ~1.1 pu then stabilizes near 1.0 pu |
| Reactive Power (Qeo) | Reactive power output of the generator | Increases from 0 pu to ~0.4 pu by t=3 s |
| Settling Time | Duration until key variables stabilize | Approximately 3 seconds post-disturbance |

This model replicates a SMIB operation with the 50MVA synchronous generator connected through a transformer to a three-phase transmission-line and fault block. Power GUI is then used at 50Hz to record the dynamic responses. Numerical data show that the load angle first increases over 0[degrees] to approximately 58° after 0.2 s, returning near 45° at t=3 s. Stator current reaches a maximum of 1.3pu, settling to around 1.1pu and active power up to 0.9pu with a short lived over shoot to 1.1pu respectively. This model validates transient stability and the effectiveness of AI-based optimization to improve grid reliability. On the whole, simulation results verify successful manipulation.

## V. Findings

**Good Damping:** The simulation result indicates that when the perturbation is applied, the load angle overshoot of synchronous generator (from 0° to 58°) decays rapidly and almost all dissipates within 3 seconds for 45°tam with high damping characteristic.

IJAMSR

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

**Robust Current Response:** The stator current peaks at the very first instant are 1.3pu around t = 0.15s, then sustain at an amplitude level of about 1.1pu, which indicates well-regulated current response in transients ascertained clearly.

**Active Power (All Times):** The active power ramps up from 0pu to about 0.9pu with a small transient overshoot at 1.1 pu followed by level off near 1.0 pu suggesting successful load following effort.

**Strong Fault Tolerance:** The transients of the fault block are well reduced by dynamic controls in the system, contributing to fast recovery of steady-state behaviours.

**AI Optimization Potential:** The incorporation of predictive analysis, powered by AI-based mechanisms, has shown good potential for real-time monitoring and adaptive control that contribute to an optimized grid reliability and stability.

## VI. Conclusion

Simulation results verify the feasibility of the proposed AI-based methodology for predicting and optimizing power system stability. The Simulink results show that the active system is intended for transient disturbance damping purpose, due to this fact we observe in the first three seconds its rotor angle bring back to 45 ◦ from -58.2 ◦ and the stator current response starts oscillating around 1.1pu. The active power response, which overshoots 1.1pu at the moment of disturbance and then settles to 1.0pu, clearly shows that the proposed control strategy is robust as well. Artificial intelligence technologies integrate to achieve the real-time status monitoring and adaptive optimization based proactive fault management, network automation function. Such findings illustrate the capabilities of AI applications to enhance dynamic stability, boost system resilience, and advance toward autonomous control in the electrical grid with higher penetration levels of green energy.

## References

1. Shah, R., Mithulananthan, N., Bansal, R. C., & Ramachandaramurthy, V. K. (2015). A review of key power system stability challenges for large-scale PV integration. *Renewable and Sustainable Energy Reviews*, *41*, 1423-1436.
2. ALShamli, Y., Hosseinzadeh, N., Yousef, H., & Al-Hinai, A. (2015, February). A review of concepts in power system stability. In *2015 IEEE 8th GCC Conference & Exhibition* (pp. 1-6). IEEE.
3. Amini, S., Pasqualetti, F., & Mohsenian-Rad, H. (2016). Dynamic load altering attacks against power system stability: Attack models and protection schemes. *IEEE Transactions on Smart Grid*, *9*(4), 2862-2872.
4. Altin, N. (2016, March). Energy storage systems and power system stability. In *2016 International Smart Grid Workshop and Certificate Program (ISGWCP)* (pp. 1-7). IEEE.
5. Liu, Y., Wu, Q. H., Kang, H., & Zhou, X. (2016). Switching power system stabilizer and its coordination for enhancement of multi-machine power system stability. *CSEE journal of power and energy systems*, *2*(2), 98-106.

IJAMSR

**International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**


6. Remon, D., Cantarellas, A. M., Mauricio, J. M., & Rodriguez, P. (2017). Power system stability analysis under increasing penetration of photovoltaic power plants with synchronous power controllers. *IET Renewable Power Generation*, *11*(6), 733-741.
7. Xu, X., Yan, Z., Shahidehpour, M., Wang, H., & Chen, S. (2017). Power system voltage stability evaluation considering renewable energy with correlated variabilities. *IEEE Transactions on Power Systems*, *33*(3), 3236-3245.
8. Keskes, S., Bouchiba, N., Sallem, S., Chrifi-Alaoui, L., & Kammoun, M. B. A. (2017, March). Optimal tuning of power system stabilizer using genetic algorithm to improve power system stability. In *2017 International Conference on Green Energy Conversion Systems (GECS)* (pp. 1-5). IEEE.
9. Honrubia-Escribano, A., Gómez-Lázaro, E., Fortmann, J., Sørensen, P., & Martin-Martinez, S. (2018). Generic dynamic wind turbine models for power system stability analysis: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *81*, 1939-1952.
10. Gupta, A., Gurrala, G., & Sastry, P. S. (2018). An online power system stability monitoring system using convolutional neural networks. *IEEE Transactions on Power Systems*, *34*(2), 864-872.
11. Flynn, D., Rather, Z., Årdal, A. R., D'Arco, S., Hansen, A. D., Cutululis, N. A., ... & Wang, Y. (2019). Technical impacts of high penetration levels of wind power on power system stability. *Advances in Energy Systems: The Large-scale Renewable Energy Integration Challenge*, 47-65.
12. Hasan, K. N., Preece, R., & Milanović, J. V. (2019). Existing approaches and trends in uncertainty modelling and probabilistic stability analysis of power systems with renewable generation. *Renewable and Sustainable Energy Reviews*, *101*, 168-180.
13. Hatziargyriou, N., Milanovic, J., Rahmann, C., Ajjarapu, V., Canizares, C., Erlich, I., ... & Vournas, C. (2020). Definition and classification of power system stability–revisited & extended. *IEEE Transactions on Power Systems*, *36*(4), 3271-3281.
14. Meegahapola, L., Sguarezi, A., Bryant, J. S., Gu, M., Conde D, E. R., & Cunha, R. B. (2020). Power system stability with power-electronic converter interfaced renewable power generation: Present issues and future trends. *Energies*, *13*(13), 3441.
15. Luo, J., Teng, F., & Bu, S. (2020). Stability-constrained power system scheduling: A review. *IEEE access*, *8*, 219331-219343.
16. Shair, J., Li, H., Hu, J., & Xie, X. (2021). Power system stability issues, classifications and research prospects in the context of high-penetration of renewables and power electronics. *Renewable and Sustainable Energy Reviews*, *145*, 111111.
17. He, X., Geng, H., & Mu, G. (2021). Modeling of wind turbine generators for power system stability studies: A review. *Renewable and Sustainable Energy Reviews*, *143*, 110865.
18. Pasiopoulou, I. D., Kontis, E. O., Papadopoulos, T. A., & Papagiannis, G. K. (2022). Effect of load modeling on power system stability studies. *Electric Power Systems Research*, *207*, 107846.
19. Gu, Y., & Green, T. C. (2022). Power system stability with a high penetration of inverter-based resources. *Proceedings of the IEEE*, *111*(7), 832-853.

**International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281**

20. Massaoudi, M. S., Abu-Rub, H., & Ghrayeb, A. (2023). Navigating the landscape of deep reinforcement learning for power system stability control: A review. *IEEE access*, *11*, 134298-134317.
21. Abo-Khalil, A. G. (2023). Digital twin real-time hybrid simulation platform for power system stability. *Case Studies in Thermal Engineering*, *49*, 103237.
22. Semertzis, I., Ştefanov, A., Presekal, A., Kruimer, B., Torres, J. R., & Palensky, P. (2024). Power System Stability Analysis from Cyber Attacks Perspective. *IEEE Access*.
23. Ibrahim, N. M., El-said, E. A., Attia, H. E., & Hemade, B. A. (2024). Enhancing power system stability: an innovative approach using coordination of FOPID controller for PSS and SVC FACTS device with MFO algorithm. *Electrical Engineering*, *106*(3), 2265-2283.
24. Saleh, A. M., Vokony, I., Waseem, M., Khan, M. A., & Al-Areqi, A. (2025). Power system stability with high integration of RESs and EVs: Benefits, challenges, tools, and solutions. *Energy Reports*, *13*, 2637-2663.
25. Ali, J. S., Qiblawey, Y., Alassi, A., Massoud, A. M., Muyeen, S. M., & Abu-Rub, H. (2025). Power System Stability with High Penetration of Renewable Energy Sources: Challenges, Assessment, and Mitigation Strategies. *IEEE Access*.