

Application of Artificial Neural Networks for Intelligent Control in Power Systems

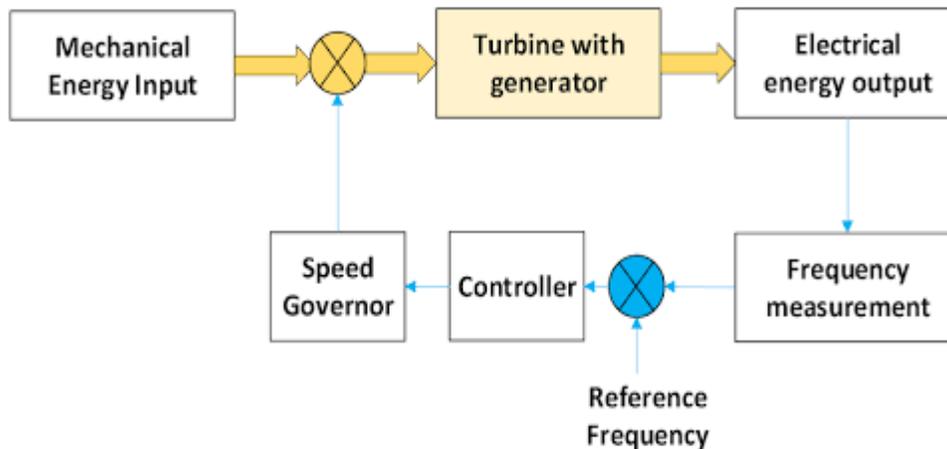
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INTRODUCTION

The modern electrical power system can be conceived of as the highest advanced infrastructure of engineering that has ever been conceived of, comprised of the subsystem of generation, transmission, distribution, and control that together must operate together to fulfill the requirements of the end-users (Murty, 2022). With the explosive rate of energy demands escalation, the integration of the renewable sources, and the ever-growing demands of being capable of providing steady and stable supply of electricity, the use of intelligent control of the power system has become the pivotal one that is needed. Intelligent control methods focus on maximizing the facilitation of further improvement of increased stability and reduction of loss by taking into account the variable and dynamic nature of the power networks. One of the highest assets of Intelligent control system is that they have the capability of responding promptly to disruptions, the intelligent control systems can also be able to accommodate nonlinearities, and they also have the ability of providing stable behavior when the conditions of operation vary, all these attributes are unlike conventional systems.

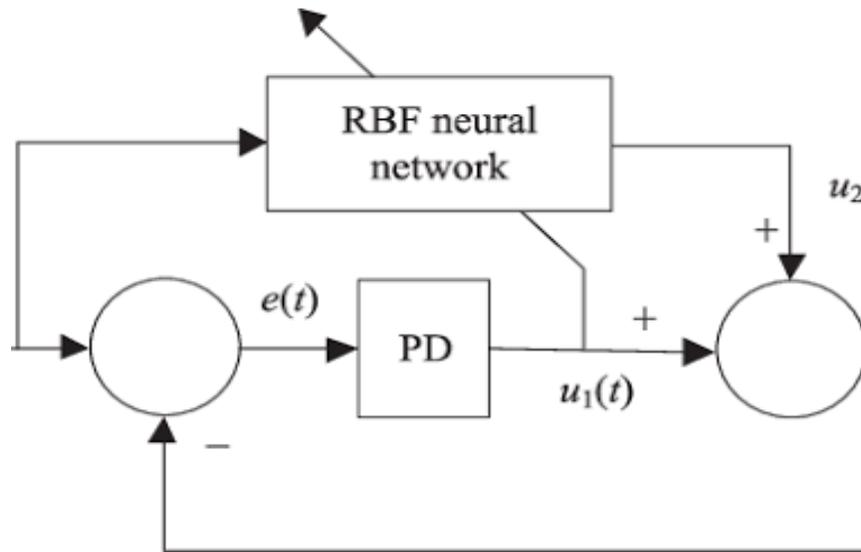


From "A Comprehensive Review of Load Frequency Control Technologies" by Rasolomampionona et al., 2024

One of the most important things about any electrical grid is that it must be stable. If it isn't, little changes can lead to bigger problems if they aren't handled properly. The old power grids were concerning the predictable, centralized generating plants where the mere stability will do with relatively simple control strategies. But the modern power grids of today have to contend with sudden load changes, distributed generating plants, as well as fault disturbances where faster and adaptive control strategies have to be used. Intelligent control provides a substitute by which the stability could be enhanced by learning the system dynamics, determining the likely disturbances, and refining the control actions on line. Other than that, effectiveness is also very much of a priority when it comes to concerning the power grids since the losses during the process of generating the powers, by the process of transmitting the powers, as well as delivering the powers result in high wastage with the corresponding effects on the production cost aside from being environmentally friendly. Intelligent methods on their own reduce the inefficiencies by optimizing the generator outputs, reducing the line losses, as well as providing the proper voltage regulations. Lastly, the dependability of the system—defined by the measure of the supply of powers without interruption aside from the fault tolerance—substantially improves when the power grid avails intelligent

methods. With the tracking of the state of the power grid at all times except the change of the control choices on the fly, the power grids that avail the methods reduce the outage apart from improving the satisfaction of the powers customers.

Despite the phenomenal addition of power systems to the development of industry and society, the traditional control methods such as the Proportional–Integral–Derivative (PID) controllers and the classical linear control methods have shown significant inadequacies when dealing with the challenges in current grids. PID controllers, for instance, have widely been used due to the benefits of simplicity, cost savings, and satisfactory performance for linear time-invariant conditions (Ullah et al., 2021). So far, power systems barely operate in optimal conditions. They are inherently nonlinear, with parameters changing relentlessly, and with stochastic disturbances such as weather conditions, fluctuating demand, and unforeseen disturbances. Therefore, the operation with the PID controllers will not ensure performance and stability when dealing with conditions altering very fast or nonlinear dynamics. This is caused by the phenomenon involving the use of fixed gains, thus becoming less effective in the conditions where adaptability is needed, as the compensation for the controllers becomes unfeasible in vast complex networks.



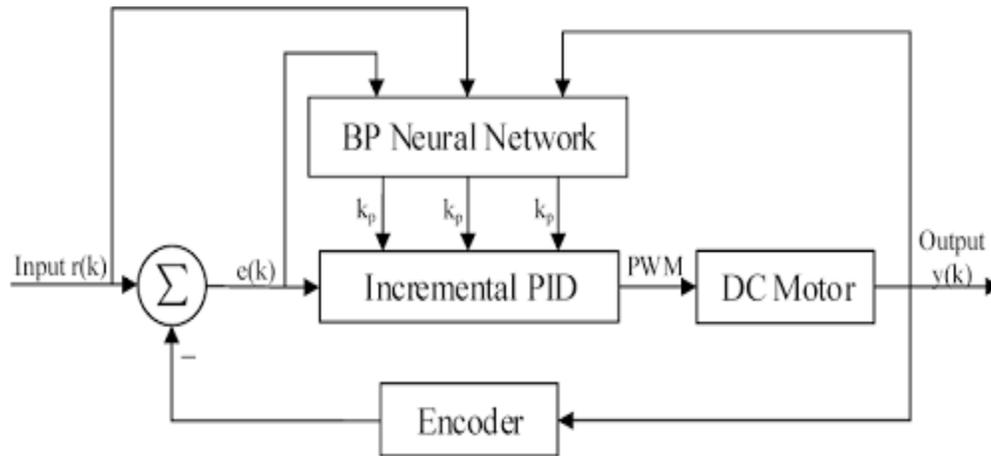
From “A Design of FGA-Based Neural Network PID Controller for Motion Control System” by Wang et al., 2022

Similarly, the conventional linear techniques for controlling the power system depend on linearity and restricted deviations close to equilibrium points, which make these techniques fail when exposed to nonlinear effects such as voltage instability, frequency oscillations, and inter-area power swings (Saleh et al., 2024). These techniques also should reduce the system model, which deforms the outputs and eliminates the capability of accurately depicting the dynamic behavior of the true power systems. That is, if the steady-state operation of the linear scheme is applicable but some unknown phenomenon such as generator loss or sudden change of loads is invoked, the scheme fails to accomplish the task effectively. Furthermore, the requirement of the accurate mathematical models is the inherent deficiency of the classical one since true models of the highly advanced systems do not come so readily. Such a divergence between the theoretical requirements and true system operations greatly renders the practical applicability of the classical techniques useless in the modern applications today.

The PID and linear controllers' weaknesses equate to the pressing need for superior techniques that can be able to support the nonlinear and adaptive nature of today's power systems. It is where the artificial neural networks (ANNs) have been a very good substitute. With the structure of the human brain, the neural net is the interconnected group of nodes that parallel-process the information and learn to accommodate the adaptation. Their promise is the ability of approximating the nonlinear complex functions that lack the explicit description in the plants' mathematical formulations. This function comes to the rescue of the power systems where the plants' dynamics are complicated to the level of the plants' conventional equations not being able to describe them (Maier et al., 2023). By learning the previous or real-time data, power systems employing the use of the neural network will acquire the patterns, abstract system behavior, and make the appropriate choices to improve performance with varying operating conditions.

One of the most appealing benefits of power system controls using neural networks lies in their flexibility. In contrast to traditional fixed-parameter controllers, ANNs can repeatedly change their internal weights by training so that they will accommodate varying conditions such as load changes, variability in renewable energy sources, or unexpected

disturbances. This flexibility ensures that the control system will perform stably and reliably even when conditions differ substantially from the baseline. To return to the previous example, when an abrupt fault arises on the power line, a controller using a neural network will immediately change excitation on the generators or transformer tap settings so as to ensure the system remains stable, but when using the fixed-gain PID controller, the system may not have the necessary flexibility.



From “A Design of FGA-Based Neural Network PID Controller for Motion Control System” by Wang et al., 2022

Another advantage of dealing with neural networks is the capability to handle multidimensional input data and give correlated control decisions. Power systems have numerous variables including voltage, current, frequency, and load profile. Using the traditional way to manipulate all the variables at once is hard on computers and takes a long time. However, it is best for the networks to handle high-dimensional data processing and finding hidden connections between the variables. This will make it possible to come up with better and more comprehensive control approaches. It makes the networks good for loads like the one that has forecasting, fault detection, stability, and voltage stabilization.

Research Objectives

The long-term aim is to investigate the application of artificial neural networks (ANNs) for the purpose of smart power system controls with an objective for raised stability, assured reliability, and improved efficacy. Although the application of traditional controls such as the Proportional–Integral–Derivative (PID) and linear control approaches has been widespread due to their wide availability, the inability to handle nonlinear as well as dynamic conditions provides the need for highly adaptive technologies. With regards to the capability for learning as well as the nonlinear approximation capability, the solution comes in the form of neural networks. From the following research targets, the current study is guided.

First is the design of a neural network model for regulating AC generators or transformers. AC generators and transformers are crucial parts of the power system, for they regulate power generations, voltage controls, and energy transmissions. Breakdown or inefficacy in the control may lead to instability, loss of energy, or complete blackouts. Most conventional controllers do not effectively address nonlinearities in the generator's excitation system or the variable load conditions that affect transformer tap changers. This study seeks to extract the intrinsic nonlinear characteristics of the components by formulating an ANN-based control model and to offer an enhanced sense of responsiveness and adaptability for regulation. During the design phase, the ANN will learn from either real or simulated operational data to find patterns, make predictions about other states, and give the best control outputs. The transformers will better control the voltage, improve the quality of the power, reduce transients, and improve the power factor because the ANN model is expected to be better than traditional methods at maintaining voltage stability, suppressing oscillations, and increasing fault tolerance.

The second objective is to enhance dynamic stability for conditions with diverse loads. Power systems today are hit by severe swings caused by variables such as increasing electricity demand, integration with renewable power, and variability on the demand side. Dynamic stability refers to the characteristic where the system is capable of sustaining synchronism performance when exposed to disturbances, either minor or major (Brik et al., 2024). Variations of loads particularly pose the challenge to the system severely due to unpredictability and the likelihood of interfering with generator action along with voltage regulation. Using the neural network control, the paper tries to construct the kind of system that can learn and react to the variations online. Due to the fact that ANNs can be made adaptive, the networks can adjust the mode of their response as the conditions evolve without the need of the corresponding explicit reprogramming. The study aims to avoid

the risk of cascade failures, decrease the system downtimes, and provide a stable supply of energy under strain by improving the quality of the dynamic stability.

The final goal of this study is to compare how well neural network-based control works with traditional control methods. Even though ANNs have a lot of theoretical potential, their improved effectiveness needs to be shown by comparing them to tried-and-true approaches like PID and linear controllers (Assani & Matic, 2025). The study will compare things like the stability margin, response time, error reduction, shock resistance, and overall effectiveness of the system. This will compare the advantages and disadvantages and the results that will be obtained will help in deciding the situations where the neural networks provide superior control and where the traditional methods are more appropriate. This comparison will therefore allow us to reach an independent balance and thus facilitate the implementation and integration of intelligent control on the future smart power systems.

It is likely that the study will have multifaceted results. First of all, the creation of the optimum generator with the transformer network structure will enable elimination and effective management of the working problems. Secondly, owing to the improvement of the dynamic stability, the power systems will be more stable against the deviations and disruptions. Third, the comparison of the performance of the traditional and neural controllers will be an indication of the practical advantage of the introduction of the ANN and may be the precursor to the broader scale application of the industry. Overall, these will be of advantage to the field of power engineering by providing wiser, adaptive, and sustainable control schemes. Outcome will also have effects on future operation and design of the power systems with particular applicability for the integration of the wind power and the intelligent grids where the robustness and flexibility are of central importance.

METHODOLOGY

The first step in the methodology is to choose the power system as the target. In this case, a single-machine infinite bus (SMIB) or a tiny multi-bus network is utilized. The SMIB approximation is employed in many studies of control and stability because it gives a simple but strong picture of how the connected generator works with the vast grid. Despite this simplified nature, the most important power system stability dynamics such as rotor angle ping-pong effects as well as voltage regulation are addressed. This renders the system appropriate for advanced control strategy testing due to its simplified assumptions. Conversely, the use of a small multi-bus network represents an advanced setup with inclusion of several generators, transformers, as well as load buses. This setup better represents the real power grids with an ability to extensively analyze the performance of the ANN in interconnected networks (Rosle et al., 2019). This selection between the use of the SMIB or the multi-bus setup is primarily on the extent of the study: the use of the SMIB is best for initial development as well as testing preliminary models. This extends the applicability of the models developed for the extent for the multi-bus setup. Finally, the current study targets the use of the SMIB setup for initial design as well as analysis due to the simplified yet clear methodology. This is with the potential to scale the findings over the multi-bus networks with the aim to exploit robustness.

Data preparation is the following crucial step in the methodology. Volumes of data are required to train and validate the neural networks for models to gain results with high reliability and accuracy. The data can either be obtained through simulation or actual operational measurements. Simulation data are generated with the help of software packages such as MATLAB/Simulink, PSCAD, or PowerFactory, capable of emulating the dynamics of power systems for varying operating conditions. One of the advantages of simulation data lies in the fact that the researchers can still maintain control of scenarios, intentionally add disturbance, and investigate the system behavior in a systematic manner. An example may be simulation of voltage instability, frequency oscillation, or load change, the derived tagged datasets being used to train the ANN effectively.

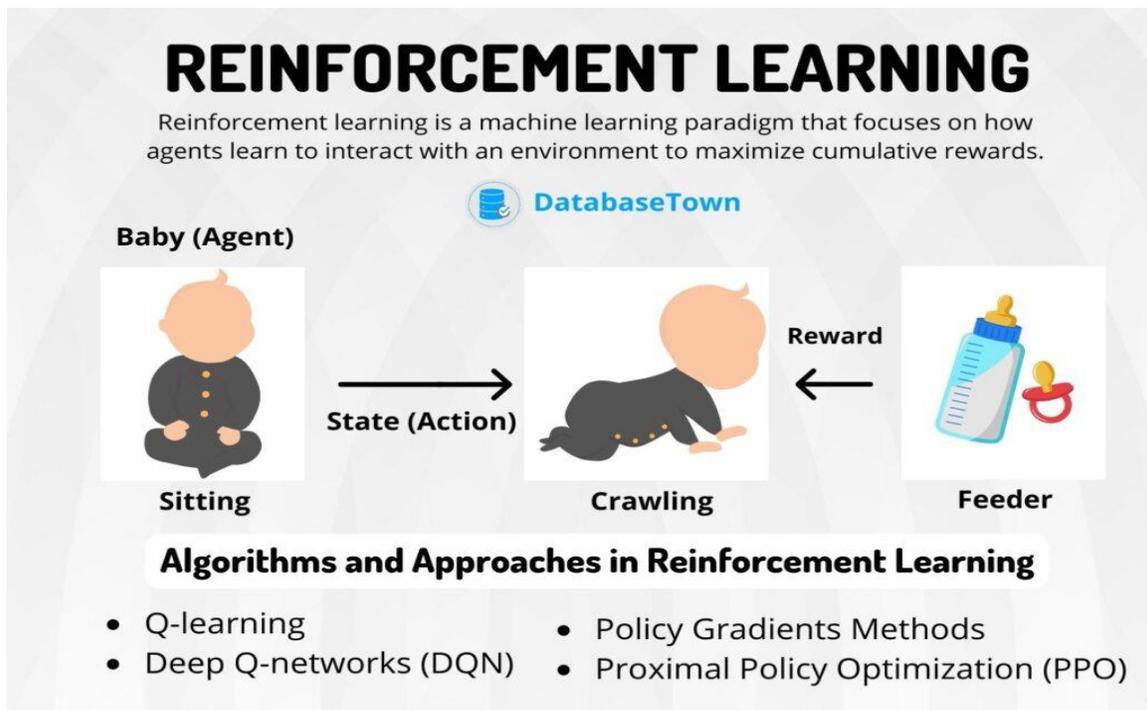
However, the real operational data, which is derived by pulling out data from phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) systems, or some sensors on real power grids, is the actual system operation. The appeal of operational data lies in the fact that it is realistic, as it preserves noise, uncertainty, and nonuniformities that might not be modeled by simulation. Operational data is also less accessible, possibly incomplete, and not easy to preprocess and clean. Simulation data is given highest priority for the initial training phase for the extraction of the baseline ANN model in this study, with operational data with us presuming that it is accessible it is therefore serving as an additional set for the checking of the trained network's generality as well as its practical performance.

Training the neural network is the key to this methodology. Some learning algorithms are discussed, such as Backpropagation, Real-Time Recurrent Learning (RTRL), and Reinforcement Learning (RL). Backpropagation is the most popular training algorithm for feedforward neural networks. This algorithm propagates the error between the predicted output and the actual output backward through the network by iteratively adjusting the weights so that the error is

minimized. Its advantage is that it is simple, efficient, and especially designed for supervised learning problems. But it has the disadvantage that it may get trapped into the local minima and that it needs big labeled datasets, which is often not available on the power system problems.

Real-Time Recurrent Learning (RTRL) extends backpropagation for recurrent networks, which are superior for handling sequence or temporal data. Power systems are, by definition, dynamical, time-varying processes, so RTRL is effective for uncovering dependencies over time. Recurrent networks using RTRL for training, for instance, are superior for representing load changes or oscillatory instability as opposed to feedforward networks. However, the major weakness with using RTRL is its high CPU demand: the larger the network, the more computationally intensive the training becomes. This might jeopardize its scalability among very large or complex power systems.

Reinforcement Learning (RL), however, is the other paradigm where the network is trained by experimenting with the environment and rewarded or penalized for its actions. It is especially helpful in control situations where the goal is to attain the long-term best solution rather than just reducing the current mistake. For example, a neural controller taught by the RL might learn how to stabilize voltage or frequency through trial and error during simulation so that it is ready to respond to changes that are not wanted. Reinforcement Learning (RL) does not require specific labeled datasets for its operation; rather, it is most effective for nonlinear dynamical systems.



From “Reinforcement Learning Basics” by Davies, 2025

The major goal of the methodology is to figure out which algorithms were best for different control tasks in the power system. Backpropagation is the best choice for basic models where the goal is to reduce complexity. RTRL is the best choice for dynamic modeling when the goal is to explore stability. RL is the best choice for scenarios that are very complex or unpredictable. There could also exist the possibility of an integration of these approaches in an attempt to harness their respective benefits.

Once the neural network model is trained, the developed model must be extensively tested for different operating conditions. Power systems encounter different conditions, yet the robustness of the ANN needs to be defined with these modifications. Load changes are also among the most frequent and challenging cases. With the change in demand throughout the day, the system must alter similarly to ensure stable voltage as well as frequency. The ANN will encounter slow changes along with sudden load changes to test its flexibility as well as quick responses.

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