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Design and Analysis of Optimal Control of Smart Nano-Grid using Renewable Resource and Neural Network Controller

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***Abstract* -- Energy storage and control is the capture of energy produced for use at a time to time. Multiple storage devices are used in nanogrids to provide power backup solutions when the distributed energy resources (DERs) are unable to supply the load demands. This work deals with the design and analysis of optimal control of smart nano-grid using renewable resource and neural network controller. It is observed that the conventional method of controller design can potentially make the system unstable. This paper proposed a neural network based controller to be considered in the design and analysis is done to ensure the stability of DC nanogrid in all operating modes with improved performance.**

***IndexTerms*-- Energy storage, NanoGrid, MPPT, Photovoltaic, Battery, Power unit.**

I. INTRODUCTION

The permeability of renewable energy in the nanogrid is relatively high, and its intermittence will lead to the fluctuation of power supply in the system. At the same time, the sudden change of load and switch will cause voltage flicker and drop of DC bus, which will threaten the stable operation of the system. The DC nanogrid composed of photovoltaic power generation, battery energy storage device, grid converter and DC and it is used as the research object load in this work, what's more, based on the bus voltage information, the operation control strategy of nanogrid is designed to realize the independent operation of the nanogrid, such as parallel in and off the grid. Tremendous advancements occurred over the next century: the development of induction and synchronous machines, electric meters, high voltage transmission, gas turbines, nuclear reactors, wind turbines, and solar photovoltaic's, to name a few. All of these technologies were turned to the development, advancement, and expansion of "the grid;" the system of large-scale centralized generation connected to energy users through a network of transmission and distribution. But while a seemingly endless supply of effort and funding was being poured into "the largest machine ever built", in recent years another trend in research started, as some began to explore the advantages to moving in the other direction: distributed, decentralized, local grids: nanogrids. Batteries and supercapacitors use dc current by their na- ture for charging and discharging.

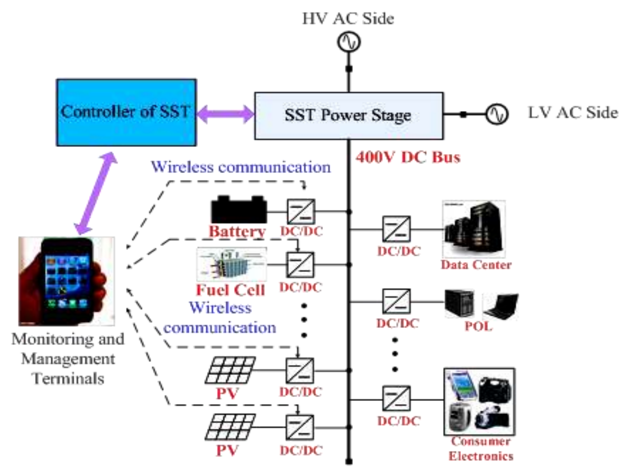

Figure 1: Schematic diagram of a DC micro/Nanogrid system

This includes the batteries in electrical vehicles, meaning dc power systems can easily integrate with vehicle-to-grid systems. In addition to the benefits of increasing electrification, another key area of research seeks to identify the most cost effective means for improving electricity access. Several studies have compared outcomes for grid extension vs decentralized generation (using an average cost for all feasible sources), grid extension vs solar home systems (SHS) , SHS vs solar photovoltaic (PV) nanogrids, and a three-way comparison between grid extension, renewable-based home systems, and renewable-based nanogrids . Each of these studies analyzes some combination of transmission, distribution, fuel, and capital costs for the RE options considered. In general, the results of these studies indicate that while grid extension is typically the least-cost option for RE, decentralized options are significantly more cost-effective in remote and/or sparsely populated areas. In particular, found that in several Sub-Saharan African nations, over 50% of the population could best be served with off-grid power systems. In addition, the rapid decline of solar PV pricing over the last few years indicates that the extent of territory where SHS and PV nanogrid systems are the best option will likely increase instead of decrease.

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Many types of electrical loads use DC power natively

The majority of electronics (such as computers, servers, and TVs) use dc power. LED lights also use dc power natively. Many types of motors and drives (especially variable speed drives) use dc power. In all three cases, these sources, storage systems, and loads require converters when- ever they interface with ac power systems; thus switching to a dc power system eliminates the need for such converters, eliminating the losses which are inherent in any type of power conversion. To date, key areas of implementation for dc power systems have included data centers, spacecraft, airplanes, shipboard power systems, traction power systems (for trains, trolleys, trams, etc), and telecommunication infrastructure. Developments in these areas have spurred research on dc nanogrids, and in some cases provided test-beds for establishing functional dc nanogrids (particularly in the case of data centers and telecoms, where the cost savings potential is significant [9].

II. PROPOSED MODEL

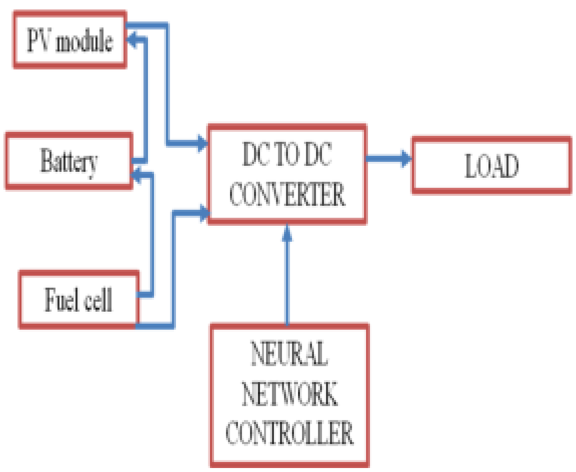

Figure 2: Model Flow Chart

Methodology Module Description

- The PV module generation.
- Input sources.
- Dc to Dc converter.
- GA and PSO Neural network controller.
- Load.

The neural network predictive controller that is implemented in the Neural Network Toolbox software uses a neural network model of a nonlinear plant to predict future plant performance. The controller then calculates the control input that will optimize plant performance over a specified future time horizon.

The first step in model predictive control is to determine the neural network plant model (system identification). Next, the plant model is used by the controller to predict future performance. (See the Model Predictive Control Toolbox documentation for complete coverage of the application of various model predictive control strategies to linear systems.). The following section describes the system identification process. This is followed by a description of the optimization process. Finally, it discusses how to use the model predictive controller block that is implemented in the Simulink environment.

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant. The prediction error between the plant output and the neural network output is used as the neural network training signal. The process is represented by the following figure:

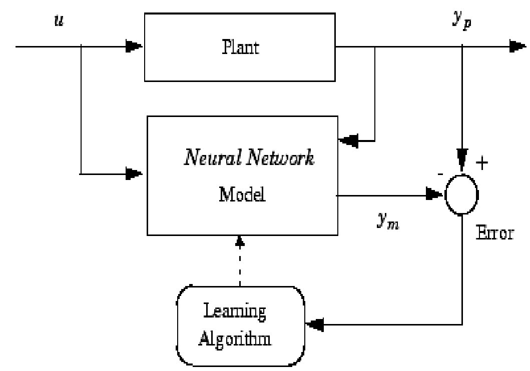

Figure 3: NN Plant

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The structure of the neural network plant model is given in the following figure.

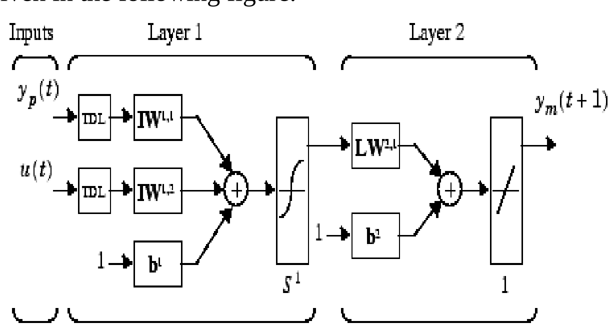

Figure 4: NN layer

This network can be trained offline in batch mode, using data collected from the operation of the plant. You can use any of the training algorithms discussed in Multilayer Neural Networks and Back propagation Training for network training.

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III. SIMULATION RESULTS

The implementation of the present model is done over MATLAB 9.4.0.813654 (R2018a). The various electrical toolbox and blocks helps us to use the functions available in MATLAB Library for various design strategy.

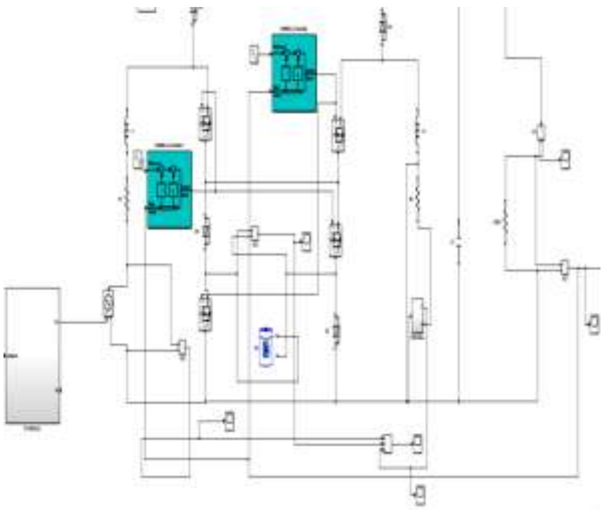

Figure 5: Proposed Model

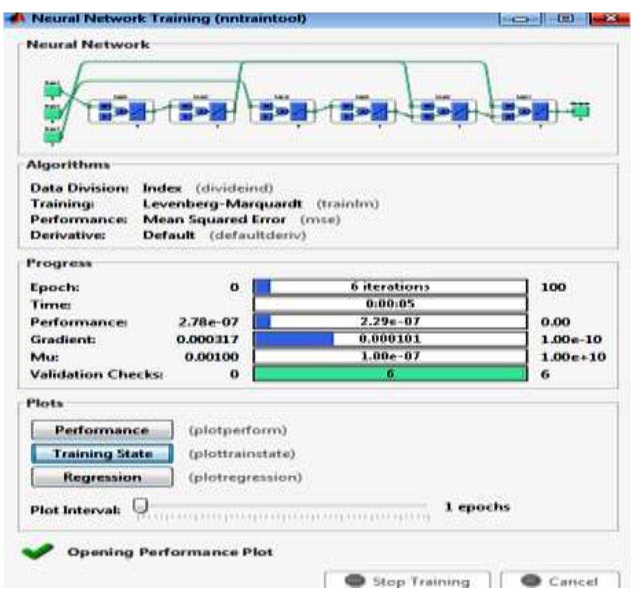

Figure 6: Neural Network Training Data

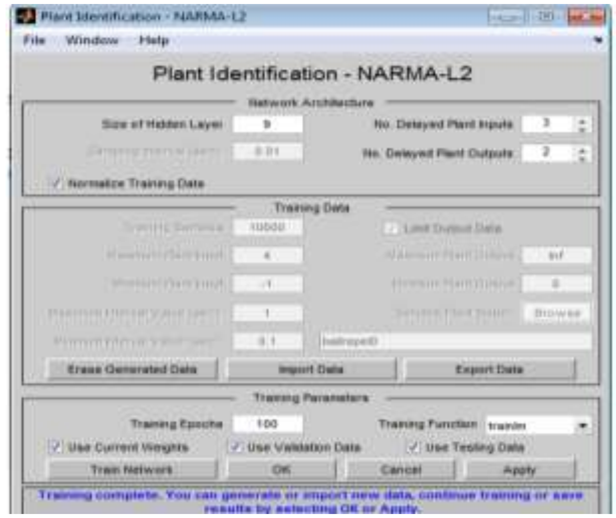

Figure 7: Neural Network Plant Identification

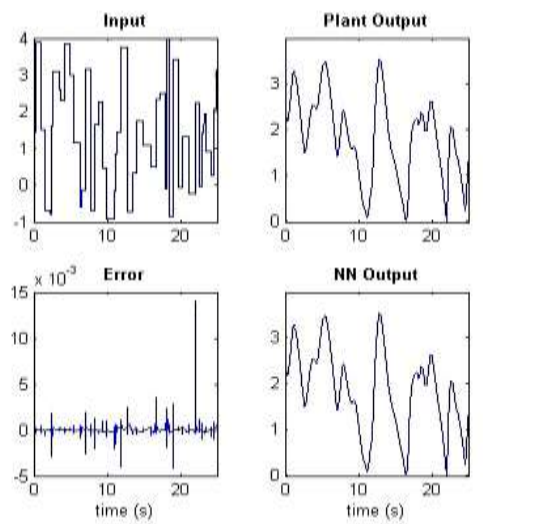

Figure 8: Training Data Output-1

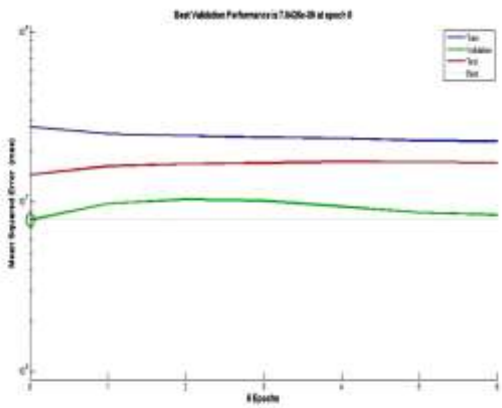

Figure 9: Validation Performance

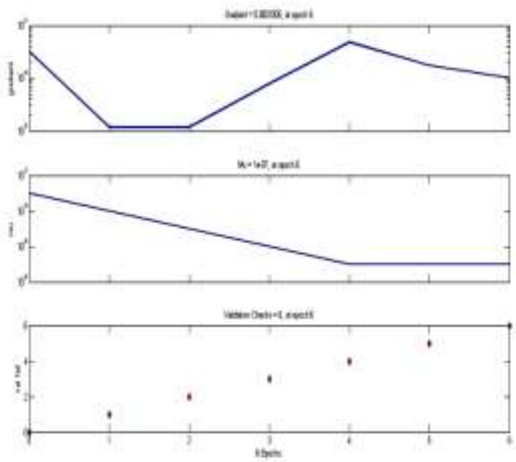

Figure 10: Validation Performance-2

Table 1:
Simulation parameters

Sr. No.	Parameters	Previous work [1]	Proposed Work
1	Controller	GA and PSO	Neural Network
2	Total Load Power	60 KW	Upto 70 KW
3	PV Power	20 KW	30KW
4	Fuel Cell Power	20 KW	40KW
5	Steady state error	6071.3W	Less than 1000W
6	Sliding mode controller	1%	0.2%
7	Time	0.267 seconds	0.1 Sec

Therefore proposed model simulation result achieves good performance.

IV. CONCLUSION

The simulation contemplates performed with the battery, PV and fuel cell models and their Neural Network controllers show that the PV, battery bank is undeniably increasingly appropriate to give power over a long timeframe. The exponential idea of its voltage discharge bend has a considerable region of stable voltage output and can be effectively used to give base power to DC loads. In any case, at whatever point there is an unexpected high prerequisite of power, the battery can't adapt to it. The neural network provides the good controlling scheme in proposed smart nanogrid system.

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