AIJREAS VOLUME 1, ISSUE 7 (2016, JULY) (ISSN-2455-6300) ONLINE
ANVESHANA'S INTERNATIONAL JOURNAL OF RESEARCH IN ENGINEERING AND APPLIED SCIENCES

ANN CONTROL BASED MICROGRID FREQUENCY AND VOLTAGE DEVIATION REDUCTION WITH ATTACHED STORAGE SYSTEM

K.VEERA KARTHIK
PG Student, Dept of EEE,
K.S.R.M College of Engineering,
Kadapa, A.P, India,
E-mail:karthik.kompala@gmail.com

Dr. K. AMARESH
Associate Professor, Dept of EEE,
K.S.R.M College of Engineering, Kadapa, A.P, India, E-mail:karanamamaresh@gmail.com

ABSTRACT:
In this paper frequency deviations are associated with renewable energy sources because of their inherent variability. We consider a micro grid where fossil fuel generators and renewable energy sources are combined with a reasonably sized, fast acting battery-based storage system. We develop ANN control strategies for frequency deviation reduction, despite the presence of significant (model) uncertainties. They are different from traditional centralized electricity networks which transmit vast amounts of electrical energy. Across long distances at very high voltages however they are similar to utility scale power distribution grids. It is critical to maintain the Frequency Voltage deviations within a small range to satisfy military operating requirements. High-speed, grid-attached storage systems such as batteries have been proposed for reducing Frequency Voltage variability.

Index Terms: *Energy storage, micro grid, ANN control algorithms, Renewable Energy source.*

1. INTRODUCTION

To improve the efficiency of micro grids and to reduce fossil fuel usage and pollution renewable energy source may be integrated with traditional micro grids [1]. Renewable Energy sources include photovoltaic power hydro power and wind power. These are clean and abundantly available energy sources. For critical installations such as military bases, security concerns have increased interest in utilizing micro grids that allow the facility to operate in islanded mode for extended period switch renewable energy sources involved.

These are clean and abundantly available energy sources. Due to the cost effectiveness of wind turbine generation (WTG), it is one of the fastest growing clean power sources [3]. However, since the output power of WTG is proportional to the cube of the (varying) wind speed, it significantly impacts system stability, and can cause large frequency and voltage (f&v) deviations in a microgrid [3]. In this paper we will focus on control of (real) power to reduce frequency deviations.

For critical installations such as military bases, security concerns have increased interest in utilizing microgrid that allow the facility to operate in islanded mode for extended periods with renewable energy sources involved. It is critical to maintain the f&v deviations within a small range to satisfy military operating requirements. High-speed, grid-attached storage systems such as batteries have been proposed for reducing f&v variability. However, due to high cost, battery sizes must be minimized and therefore may saturate during transients, aggravating f&v deviations. In such situations, conventional control approaches are no longer sufficient to constrain these deviations within a small range, and at the same time limit the battery size. More sophisticated ANN control algorithms [4] are needed to achieve better performance despite unexpected disturbances and model uncertainties.

Our work develops ANN control strategies[5] for both the battery and conventional generation systems[6], with controllers designed to minimize battery size while at the same time significantly reducing frequency variation, despite variable loads in the microgrid, and the incorporation of a WTG source[7]. Our controllers are designed to cope with load transients, WTG output fluctuations, model uncertainties and measurement noise/errors.

2. SYSTEM SETUP AND MODELING

A typical setup of a microgrid with storage system is shown in Fig. 1. The energy sources include both conventional and renewable generation systems. On the common bus-bar are energy sources, variable loads, and also a battery-based storage system. The green blocks indicate that particular component is under control for desired performance. This system can be readily extended into more complex microgrids, with additional generators, loads, bus-bars, transmission lines, and storage systems.

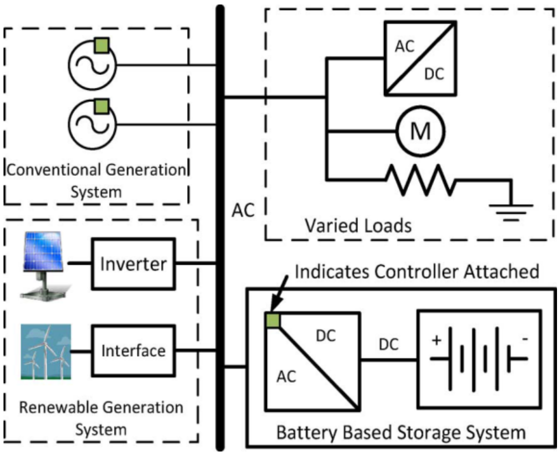


Fig. 1. Structure of microgrid with attached storage system.

The essential idea is to increase the usage of renewable energy, and so reduce the fossil fuel consumption, while at the same time maintaining system stability. Here system stability is reflected by incurring only limited system frequency deviations, despite the presence of significant transients. Low frequency load transients are handled by conventional generators (utilizing diesel or natural gas engines as their prime mover). The attached storage system can react much more quickly to load transients, and so it is primarily used for suppressing the high frequency [6] load transients caused by renewable energy sources. In order to maintain the nominal frequency in such a system, more advanced control techniques are required to deliver the system performance requirements.

In order to minimize the frequency deviation ( ), a mathematical model is used for system analysis and controller design. This model consists of three parts: conventional generator (CG), storage system (SS) and Wind Turbine Generator (WTG).

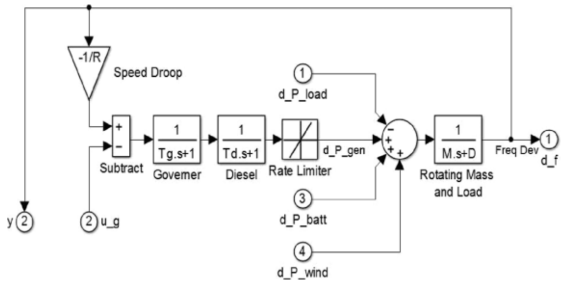


Fig.2. Conventional generator (Small Power System) model

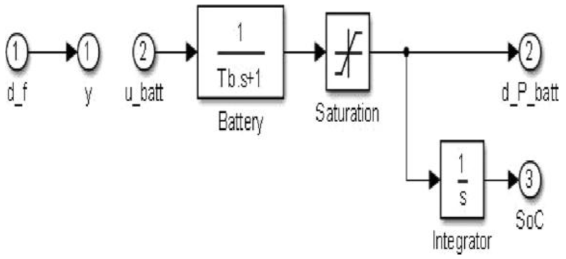


Fig.3. Battery model

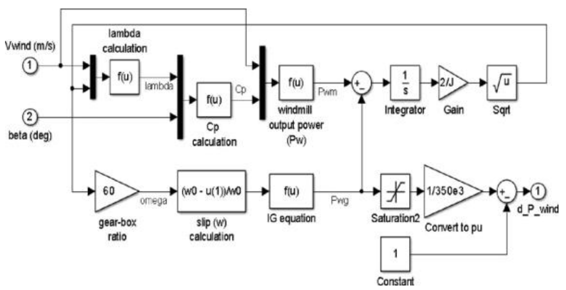


Fig.4. Wind turbine generator model.

The corresponding Simulink™models are shown in Figs. 2 – 4. Note that in order to limit the model complexity, simple transfer functions models are used for each of these blocks in the controller design process. However these models still capture the essential power/frequency tradeoffs in such systems. Since is caused by the imbalance between the power generated and the power consumed by the load, signals in the model are first normalized to per-unit (pu), and then shifted to deviations around '0' (corresponding physically to deviations from nominal 60 Hz [9]). Hence, the load variation, the SS output variation and WTG output variation [7] are denoted as: ΔPbatt, ΔPload and ΔPwind respectively. These three signals are summed at the summing block in the CG model along with the CG output variation ΔPgen. Note, during the charging or discharging periods, a battery based storage system acts as load or generation correspondingly.

In our model, ΔPbatt and ΔPbgen are controlled power deviations, as shown in Figs. 2 and 3; the control signals are 'ug' and 'ubatt' respectively. Δf is considered as the error signal. The controller receives measurements 'y' and outputs actuation/ control signals 'u'. Although ΔPbatt is a controlled output, the output is limited by a saturation block so as to prevent fast charge and discharge. In addition, the State of Charge (SoC) variation of the SS is modeled by integrating its output power deviation. It is controlled indirectly by commanding ΔPbatt.

Meanwhile, ΔPload and ΔPwind are considered as perturbations to the system in the robust controller synthesis methodology. There is no control over these two signals. Here, the controlled outputs are used for minimizing Δf, regardless of how the perturbations vary. Other renewable sources can be handled in a similar fashion.

A real wind profile is used here with a sample time of 50 ms simulated for 500 s. The WTG actual output power (Pwind) is normalized by its rated output (Pwg) and again shifted to deviations around "0" (in the linear model). is "0" unless the angular speed of the gearbox output is higher than the synchronous angular speed. A fixed pitch angle of 10 is used.

Our controller does not command the WTG, rather the WTG produces power according to the given wind speed profile (and hence acts as an unknown "disturbance" as far as our system is concerned). Tip speed ratio (λ), power coefficient (Cp), windmill output (Pwm), Slip (s) and WTG output power (Pwg) as shown in Fig. 4, and are given as: λ= Rw.w/Vwind ;Cp = f(λ , β)[14]; Pwm = Cp = f(λ , β) Vw3ρA/2 ; Ss = (w0 w)/w0;Pwg = -3V2 Ss (1+Ss)R2/(R2 – SsR1)2 + (X1 +X2)2,where is the wind speed, A is windmill rotor cross section area, w0 is synchronous angular speed, and w is angular rotor speed for a windmill.[Table-1]

Table 1

Model Parameters

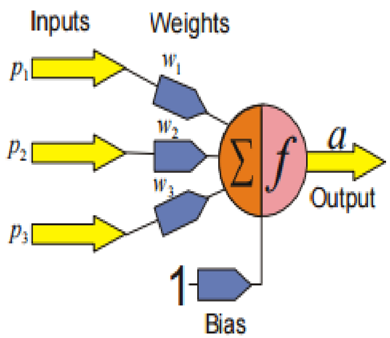
Conventional generator parameters:	
Governor time constant T_g	0.1 s
Diesel engine time constant T_d	5.0 s
Inertia constant M	0.15 $puMWs/Hz$
Damping constant D	0.008 $puMW/Hz$
Speed droop R	3.0 Hz/pu
Storage system parameters:	
Battery time constant T_b	0.1 s
Wind turbine generator parameters:	
Blade radius R_w	14 m
Inertia coefficient J	62.993 kgm^2
Air density ρ	1.225 kg/m^3
Rated output P_{wg}	350 kW
Phase voltage V	692.82 V
Stator resistance R_1	0.00397 Ω
Stator reactance X_1	0.0376 Ω
Rotor resistance R_2	0.00443 Ω
Rotor reactance X_2	0.0534 Ω
Control system parameters:	
Number of measurements	3
Number of controls	2

3. ENERGY STORAGE

Power demand varies from time to time and the price of electricity changes accordingly. The prices for electricity at peak demand periods are higher and at off-peak periods lower. This is caused by differences in the cost of generation in each period. During peak periods when electricity consumption is higher than average, power suppliers must complement the base-load power plants with less cost-effective but more flexible forms of generation, such as oil and gasify red generators. During the off-peak period when less electricity is consumed, costly types of generation can be stopped. This is a chance for owners of EES systems to benefit financially. From the utilities' viewpoint there is a huge potential to reduce total generation costs by eliminating the costlier methods, through storage of electricity generated by low-cost power plants during the night being reinserted into the power grid during peak periods. With high PV and wind penetration in some regions, cost-free surplus energy is sometimes available. This surplus can be stored in EES and used to reduce generation costs. Conversely from the consumers' point of view EES can lower electricity costs since it can store electricity bought at low off peak prices and they can use it during peak periods in the place of expensive power. Consumers who charge batteries during off-peak hours may also sell the electricity to utilities or to other consumers during peak hours.

4. ANN STURUCTURES

Artificial Neural networks (ANN) are simplified models of biological neuron[4-5] system. It consists of a massively parallel distributed processing system made of highly interconnected neural computing elements called as "Neurons", which has the ability to learn and thereby acquire knowledge. The architecture is inspired from structure of cerebral cortex of brain (Tsoukalas and Uhrig, 1997). The pioneering work of McCulloh and Pitts (1943) was foundation of NN architectures. Followed by this was Hebb (1949) who presented a mechanism for learning in biological neurons. ANN comprises of number of neurons which forms the basic processing unit. Each neuron is further connected to other neurons by links. Every neuron receives number of inputs which are modified by 'weights'. The synaptic weights would either strengthen or weaken the signal which is processed further. To generate the final output the sum of the weighted output is passed on to a non-linear filter called as 'activation function' or 'Transfer function' or 'Squash function' , plus a threshold value called 'bias' which releases the output. Figure- 5 shows the model of ANN.



$$a = f(p_1w_1 + p_2w_2 + p_3w_3 + b) = f\left(\sum p_iw_i + b\right)$$

Fig 5: ANN model

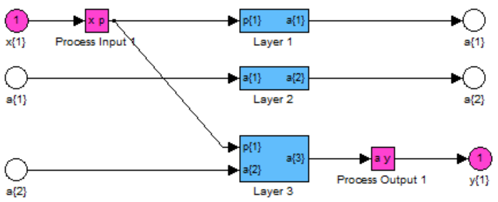


Fig-5(a): Model for ANN in LAYERS

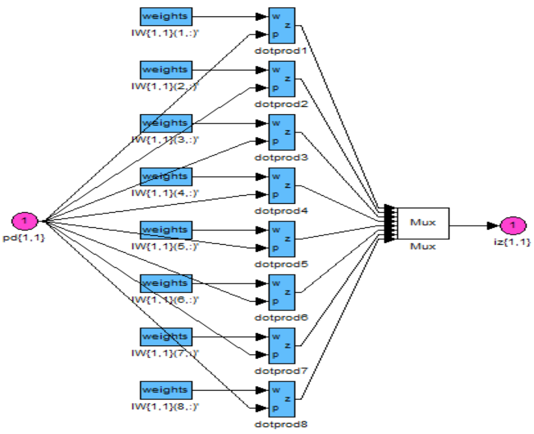


Fig-5(b): Basic model and structure in the form of weights in layers

The function of neural network is determined by structure of neurons, connection strengths, and the type of processing performed at elements or nodes. In classification tasks, the output being predicted is a categorical variable, while in regression problems the output is a quantitative variable. Neural network uses individual examples, like set of inputs or input-output pairs, and appropriate training mechanism to periodically adjust the number of neurons and weights of neuron interconnections to perform desired function. The learning methods for NN can be classified as: 9 Supervised learning, wherein the input and output patterns are provided. A teacher is assumed to be present during learning process, when a comparison is made between network's output and correct expected output, so as to determine the error. 9 Unsupervised learning, wherein the target output is not presented to the network. The system learns by itself by adapting to the structural features in input patterns. 9 Reinforced learning, a teacher though available does not present the expected answer but only indicates if the computed output is correct or incorrect. The information helps in learning process.

V. RESULTS

The load and WTG output variations have steep transients in this time interval, and the load and output power of each power source are compared in Fig. 7-8, which shows individual generation/load power deviations from the nominal value. For instance, as shown in Fig. 7, the generator increases its output power by 7% to match the 5% increase in load and 2% decrease in wind generation. The generator output follows the net load (combined load and WTG) variations and provides the major portion of power. The battery is reacting to the high frequency transients while keeping its SoC around the desired operating point.

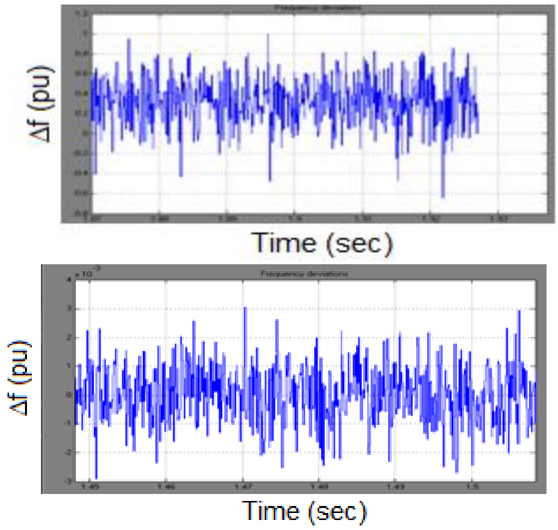


Fig-6: Frequency deviation with battery storage

Fig-10: Frequency deviation with only PID controller

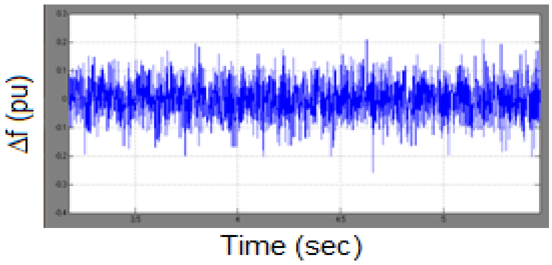


Fig-11: Frequency deviation, with 0% battery

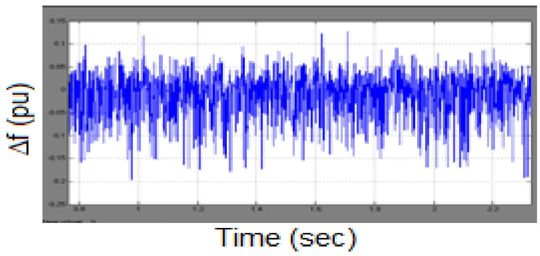


Fig-12: Frequency deviation, with 3% battery

Nominal models of the small power system and battery are shown in Figs. 2 and 3. Multiplicative model uncertainties of 5%and 3% are added to

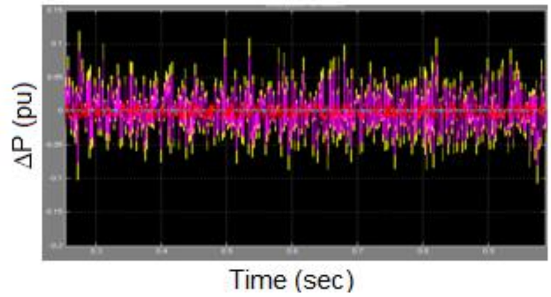


Fig-7: Battery, load, generator, wind power

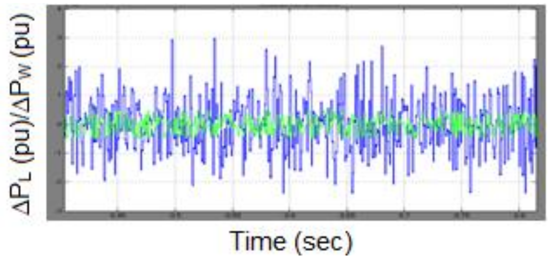


Fig-8: Load & wind deviation

model blocks 'Diesel' and 'Rotating Mass and as SoC signals. In addition, control signal penalty weights are also included. Load' to represent modeling errors. Unmodeled high frequency dynamics can also be included. Additional perturbations [12]. Measurement noise is added to the frequency deviation and

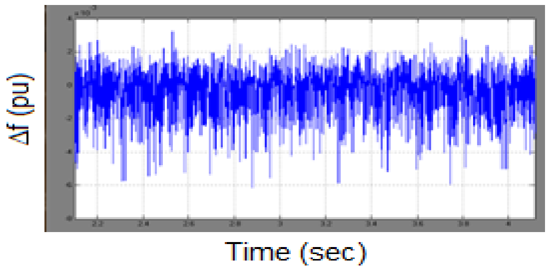


Fig-13: Frequency deviation, with 100% battery

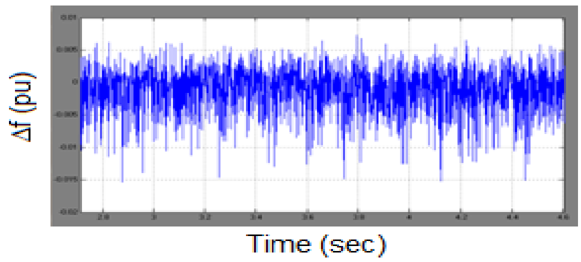


Fig-14: 10% uncertainity in diesel generator & mass & wind gust-with u-synthesis

Note that there are three control signals; the first one is designated for low frequency diesel engine control, the second one is assigned for high frequency battery control, and the third one is used for maintaining the battery at 50% of its SoC.

Our approach utilizes u -synthesis for the controller design, and careful weight selection is crucial, to enforce good tradeoffs in the

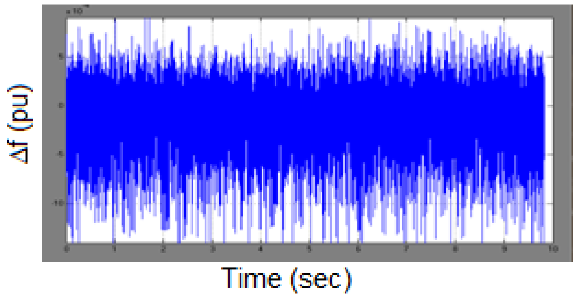


Fig-17: Frequecny deviation with only ANN controller

6. CONCLUSION

This paper presents a simulation based model of combining a small battery with a sophisticated robust control algorithm; one can significantly reduce system frequency deviation in a microgrid. In other words, specifying a certain allowable frequency deviation, the ANN control approach allows us to deliver that performance level whilst utilizing a smaller battery. Since battery- based storage systems are very expensive, this is a significant advantage.

REFERENCES

[1] The Smart Grid: An Introduction, U.S. Department of Energy, 2008 [Online]. Available: http tion.html

[3] T. Goya, E. Omine, Y. Kinjyo, T. Senjyu, A. Yona, N. Urasaki, and T. Funabashi, "Frequency control in isolated island by using parallel operated battery systems applying h-inf; control theory based on droop characteristics," *IET Renewable Power Generat.*, vol. 5, pp. 160–166, Mar. 2011.

[4]J. Hertz, A. Krogh, R.G. Palmer, "Introduction to the theory of Neural Computation", Addison-Wesley, 1991.

[5]C.M. Bishop, "Neural Networks for pattern recognition", Oxford University Press, New York, 1995.

[6] F. Daneshfar and H. Bevrani, "Load-frequency control: A ga-based multi-agent reinforcement learning,Generation" Transmission. Distribution, IET, vol. 4, pp. 13–26, Jan. 2010.

[7] R. Gagnon, G. Turmel, C. Larose, J. Brochu, G. Sybille, and M. Fecteau, "Large-scale real-time simulation of wind power plants into hydro-quebec power system," in Proc. 9th Int. Workshop Large-Scale

controller (fig-6 to fig-15). During the controller design process, since the model un- certainties and system performances are considered at the same time, system robustness and performance is well balanced. The battery based storage system is constantly charged or discharged to deal with fast transients. At the same time it is necessary to keep the SoC around 50%, which the MIMO controller does [10].

Integrat. Wind Power into Power Syst. Transmiss. Networks for Offshore Wind Plants, Quebec City, Canada, 2010.

[8] T. Senjyu, R. Sakamoto, N. Urasaki, T. Funabashi, H. Fujita, and H. Sekine, "Output power leveling of wind turbine generator for all operating regions by pitch angle control," IEEE Trans. Energy Convers.,, vol. 21, pp. 467–475, Jun. 2006.

[9] D. Rerkpreedapong, A. Hasanovic, and A. Feliachi, "Robust load frequency control using genetic algorithms and linear matrix inequalities," IEEE Trans. Power Syst., vol. 18, pp. 855–861, May 2003.

[10] M. Anderson, M. Buehner, P. Young, D. Hittle, C. Anderson, J. Tu, and
D. Hodgson, "MIMO robust control for HVAC systems," IEEE Trans.
Contr. Syst. Technol., vol. 16, no. 3, pp. 475–483, 2008.

[11] H. Koc, D. Knittel, M. De Mathelin, and G . Abba, "Modeling and robust control of winding systems for elastic webs," IEEE Trans. Contr Syst. Technol., vol. 10, no. 2, pp. 197–208, 2002.

[12]Z.-Q. Wang and M. Sznaier, "Robust control design for load frequency
control using /spl mu/-synthesis," in *Proc. Southcon/94. Conf. Rec.*,
Mar. 1994, pp. 186–190.