ARTIFICIAL NEURAL NETWORK CONTROLLER TOPOLOGY FOR GRID-TIED PHOTOVOLTAIC POWER GENERATION SYSTEM WITH DC VOLTAGE DROP CONTROL

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ABSTRACT:

In this project the integration of Photovoltaic (PV) power generation systems into the electrical grid is gaining significant importance in the context of renewable energy sources. To enhance the performance, stability, and efficiency of grid-tied PV systems, this paper presents an innovative controller topology utilizing Artificial Neural Networks (ANNs) in conjunction with DC voltage droop control. Traditional grid-tied PV systems employ conventional control strategies that may not fully exploit the capabilities of the system under varying operating conditions. In this study, we propose a novel approach that leverages ANNs to optimize the control of PV inverters. ANNs, with their ability to model complex nonlinear relationships, are employed to predict the optimal reference voltage and current set points for the inverter to maximize energy production and grid stability.

Keywords: Grid-connected photovoltaic power generation system, Dc voltage drop control, inertia characteristic, damping effect, synchronization ability, neural networks.

I INTRODUCTION

The world's nations have come to the understanding that creating clean energy should be a top priority due to the growing severity of the environmental degradation and global energy problem. Extensive development has been done on electric vehicles, FACTS equipment, and renewable energy generation. Due to its advantages of being pollution-free and having an abundance of resources, grid-tied photovoltaic power generation has experienced rapid growth as a representative of renewable energy power generation technology. The rotational synchronous generator (RSG), which is the primary source of power generation in a traditional power system, possesses significant damping capacity and huge inertia. The grid-connected inverter's physical attributes clearly differ from RSG's in a grid-tied photovoltaic power generation system. Having no physical inertia, the grid-tied inverter is a power electronic device. It has low inertia and weak damping when linked to the grid on a wide scale, which reduces the power system's inertia and poses serious risks to the grid's ability to operate safely and steadily. In addition, photovoltaic power output is very volatile, highly unpredictable, and clearly intermittent, all of which have a negative impact on the power grid's ability to operate steadily. As a result, in order to supply inertia when photovoltaic power is integrated into the power grid, they often need to include a particular quantity of energy storage.

The combination of solar power generation and energy storage system has been chosen as the research object in, where design and control strategy research is carried out to enhance the system stability of the grid-integrated photovoltaic power generation. Nevertheless, the energy storage system is less efficient in the event of minor disruptions, and the enormous potential of primary energy and its converter in the modelling of inertia and damping characteristics is not fully utilised. According to, the grid-tied inverter's DC side capacitor exhibits dynamic behaviour characteristics that are comparable to those of the RSG rotor. Additionally, the grid-tied inverter's DC side capacitor voltage can fluctuate within a specific range, offering a certain amount of inertia support.

However, it omitted an analysis of the system's overall inertia, damping, and synchronisation properties, including the dynamic of the capacitor. The grid-tied inverter in the new energy grid-tied power generation system and the RSG in the traditional power generation system have an equivalent dynamic model and a similar physical mechanism, according to , which also demonstrates how the grid-tied new energy power generation system corresponds with the traditional power generation system from the standpoint of electromechanical transient process modelling.

The inertia, damping, and synchronisation characteristics of the grid-tied converter system under voltage and current double closed-loop control are analysed, and an SSG model that is appropriate for the analysis of the DC voltage time scale dynamic characteristics of the system is proposed. The mechanism of a static synchronous compensator for reducing the power oscillation of the power grid is examined in by developing the SSG model. By completely utilising the converter's idle capacity, the rapid power compensation (RPC) based frequency control approach is created in to maximise the converter's ability to correct for grid imbalance power. The RPC technique outperformed droop control in terms of frequency deviation suppression, as shown by the mathematical evidence, and in terms of RoCoF suppression versus inertia control, with identical converter capacity limit.

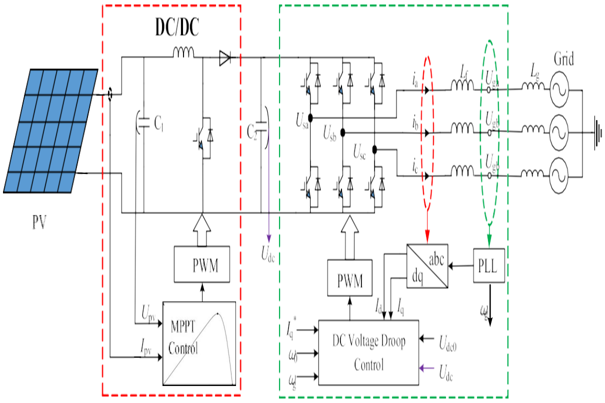

Fig.1. Grid-connected photovoltaic power generation system based on DC voltage droop control.

The analysis method based on the SSG model is applied to study the grid-tied energy storage system's inertia and damping properties under two distinct control schemes. In order to study the inertia, damping, and synchronisation characteristics of the grid-tied photovoltaic power generation system that is controlled by the DC voltage droop control, this paper establishes the SSG mathematical model. It then uses the electrical torque analysis method to derive the system equivalent parameter expression and elaborates on the function law of the parameter from the level of mathematical analysis and physical mechanism.

The work established a theoretical foundation for the design of pertinent parameters for the grid-tied photovoltaic power generating system and demonstrated that some modifications to the traditional control methods can also alter the system's inertia and damping characteristics.

II. PROBLEM FORMATION

The instantaneous current can be written as

is(t) = iL(t) – iC(t) ----------------- (1)

Source voltage is given as

Vs(t) = Vm sin ωt ------------------ (2)

If a non-linear load has applied, then the load current will have a fundamental component and harmonic components that can be represented by

$$i_{L(t)} = \sum_{n=1}^{\alpha} In\sin(n\omega t + \emptyset_n)$$

$$i_{L(t)} = I_{1\,\sin(n\omega t+\emptyset_1)} + \sum_{n=2}^{\alpha} \sin(n\omega t + \emptyset_n)$$

----------(3)

The instantaneous load power can be given as

$P_{L(t)} = v_{s(t)} * i_{l(t)}$

$V_m I_1$ sinωtωt*+$V_m I_1$sinωt*cosωt*sin$\emptyset_1$+Vmsinωt* $\sum_{n=2}^{\infty}\sin(n\omega t + \emptyset_n) = P_{f(t)} + P_{r(t)} + P_{h(t)}$

---------(4)

From (3.2.4), the real (fundamental) power drawn by the load is

$P_{f(t)} = V_m I_1 sin^2\omega t * cos\emptyset_1 = v_s(t) * i_{s(t)}$------(5)

From (3.2.5), the source current supplied by the source, after compensation is

$i_s(t) = P_{f(t)} / v_{s(t)} = I_1 \cos\emptyset_1 \sin\omega t = I_m \sin\omega t$ ------(6)

Where $I_{sm} = I_1\cos\emptyset_1$

There are also some switching losses in the PWM converter, and hence the utility must supply a small capacitor leakage and converter switching losses in addition to the real power of the load. The total peak current supplied by the source is therefore,

$Isp = I_{sm} + I_{sl}$ ------------(7)

If the active filter provide total reactive and harmonic power. At this time, the active filter must provide following compensation current:

$I_{c(t)} = I_{l(t)} - I_{s(t)}$

Hence, for accurate and instantaneous compensation of reactive and harmonic power it is necessary to estimate, i.e., fundamental component of the load current as the reference current.

III PI CONTROLLER BASED PHOTOVOLTAIC POWER GENERATION SYSTEM WITH DC VOLTAGE DROOP CONTROL

PI controllers have advanced significantly as a result of the development of electronic control systems in the middle of the 20th century. Harold Black created the negative feedback amplifier in the 1940s, enabling more exact control over electrical systems. Modern PID (proportional-integral-derivative) controllers, which use a derivative term to increase system stability, were made possible as a result of this.

Since then, process control, robotics, and automation are just a few of the engineering applications that have made extensive use of PI controllers. They are prized for being straightforward, simple to operate, and efficient in controlling processes with a range of dynamics and disruptions.

More complex control systems, such as adaptive and model-based predictive controllers, have been made possible recently by developments in computers and machine learning. The rotational synchronous generator (RSG), which is the primary source of power generation in a traditional power system, possesses significant damping capacity and huge inertia.

The grid-connected inverter's physical attributes clearly differ from RSG's in a grid-tied photovoltaic power generation system. Having no physical inertia, the grid-tied inverter is a power electronic device. It is extensively integrated into the grid and has low inertia and weak damping, which reduces the power system's inertia and poses serious risks to the grid's ability to operate safely and steadily . In addition, photovoltaic power output is very volatile, highly unpredictable, and clearly intermittent, all of which have a negative impact on the power grid's ability to operate steadily. Consequently, when solar energy is included into the electrical system, To create inertia, they often need to have a specific quantity of energy storage.

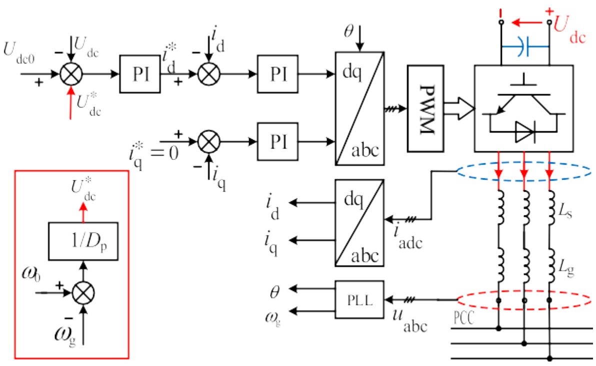

Fig.2. PI controlled Photovoltaic power generation system

In the DC voltage control time scale, ignoring the dynamic process of the inner current control loop, the control process shown in Figure 3 can be described as: where Kp and Ki represent the proportional and integral coefficients of the outer DC voltage loop, respectively; Udc∗ represents the deviation of the DC voltage. The deviation of the DC voltage can be described as:

$$U*dc = 1/Dp(\omega g - \omega 0) \quad \text{------------- (8)}$$

where Dp represents the DC voltage droop coefficient

RESULTS:

SIMULATION RESULTS WITH DROOP

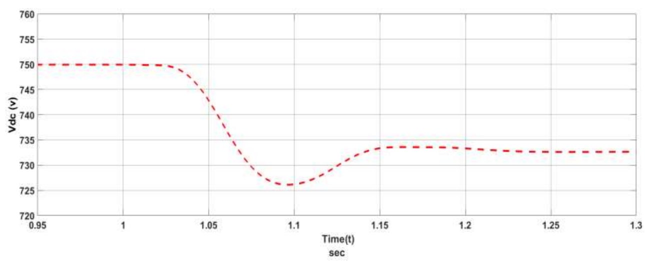

Fig.3. DC voltage variation with droop control

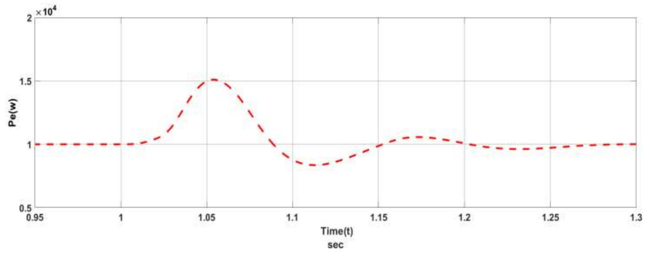

Fig.4. Power variation with droop control

SIMULATION RESULTS WITHOUT DROOP

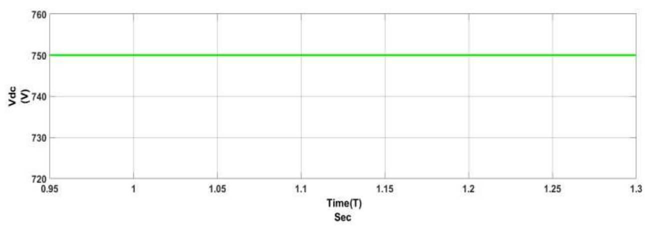

Fig.5. DC voltage variation without droop control

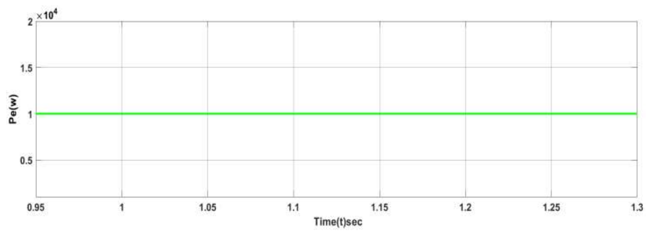

Fig.6. Power variation without droop control

From the above figures, we can observe the DC voltage and active power variations in with droop control and constant voltage and power are observed in the without droop control.

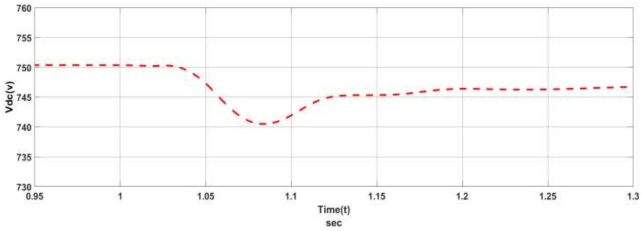

Fig.7. Influence of droop coefficients Dp on DC voltage (Vdc) at Dp = 60

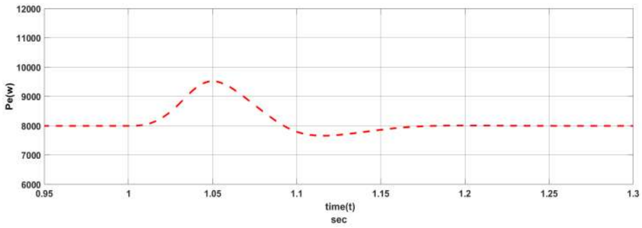

Fig.8. Influence of droop coefficients Dp on power (Pe) at Dp = 60

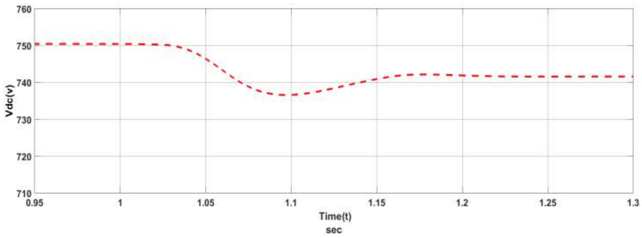

Fig.9. Influence of system inertia Kp on DC voltage (Vdc) at Kp=75

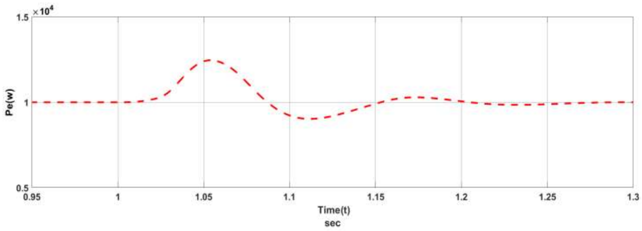

Fig.10. Influence of system inertia Kp on DC power (Pe) at Kp=75

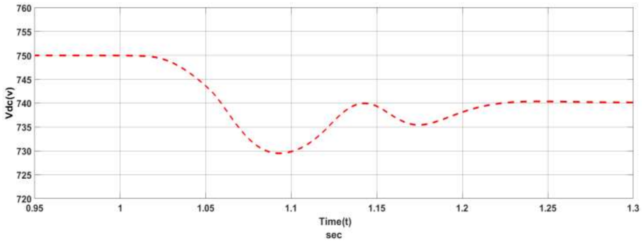

Fig.11. Influence of system inerti Ki on DC voltage (Vdc) at Ki = 100

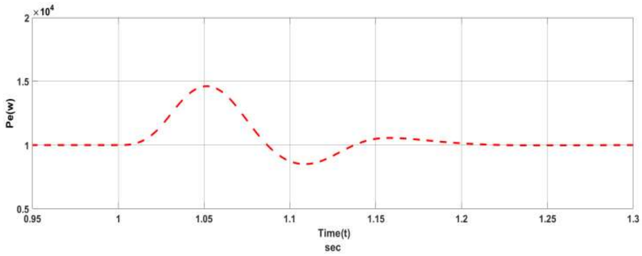

Fig.12. Influence of system inerti Ki on DC power (Pe) at Ki = 100

IV ANN BASED POWER GENERATION SYSTEM WITH DC VOLTAGE DROOP CONTROL

Artificial Neural Network (ANN) controllers have a long history, dating back to the early days of computer science and artificial intelligence. The first ANN controller was developed in the 1940s by Warren McCulloch and Walter Pitts, who created a simple model of the brain using interconnected artificial neurons.

Over the years, ANNs have evolved and become more complex, with the development of new algorithms, architectures, and training techniques. In the 1960s and 1970s, researchers developed the backpropagation algorithm, which is still widely used today for training ANNs. In the 1980s and 1990s, researchers developed new architectures, such as the multilayer perceptron and recurrent neural networks, which allowed ANNs to handle more complex problems.

ANN controllers have been used in a wide range of applications, including control systems, robotics, image processing, and natural language processing. In the 1990s, researchers began to explore the use of ANNs in adaptive control systems, which could learn and adapt to changing environments. This led to the development of techniques such as reinforcement learning, which uses ANNs to learn optimal control policies through trial and error.

The accuracy and precision with which harmonic components are removed from the distorted current waveform determines the performance of a shunt active power filter. To achieve optimal performance in removing harmonic components from the voltage or current waveform, a shunt active power filter control method has been devised. ANN controllers are introduced in this research work because of their learning ability, high speed recognition, and ability to adapt to any system. Conventional PI controllers are typically used to regulate this voltage, but they have limitations such as the time-consuming and difficult process of detecting PI parameters, as well as other drawbacks like the inability to improve the transient response of the system. A mathematical model modelled after a biological neural network is called an artificial neural network (ANN).

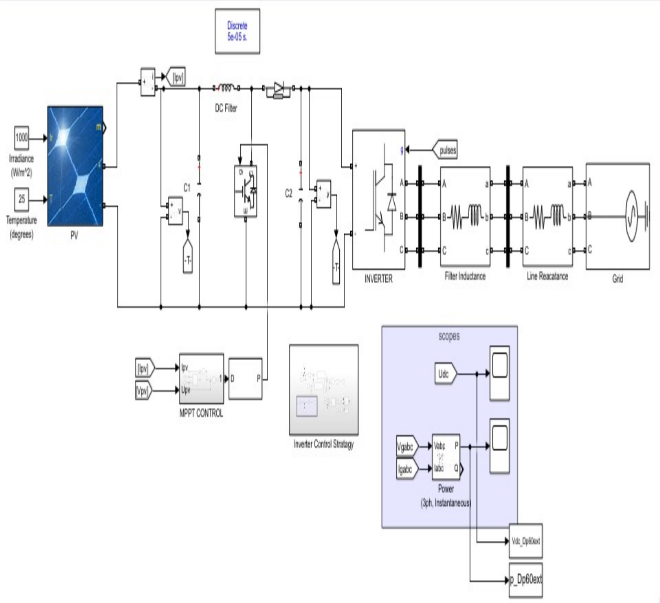

Fig.13. Grid-connected photovoltaic power generation system based on DC voltage droop control

It is similar to the brain in two ways: (i) The learning process is how the network gathers the data. (ii) The data is stored using the strengths of interneuron connections. The MATLAB workspace has the vast amount of DC-link voltage data for the "n" and "n-1" intervals obtained via the traditional method. After that, the ANN Controller is trained using this data that has been retrieved. In order to process the information, the number of neurons in the input and output layers is essentially fixed. In every training session, six of these validation checks are removed along with seven hidden layers that undergo 1000 iterations to reduce the likelihood of errors occurring.

In the case of SAPF, quick processing of the reference signals and quick identification of the disruptive signals with high accuracy are necessary for the intended compensation.

The accuracy and precision with which harmonic components are extracted from distorted current waveforms determines the shunt active power filter's performance. The shunt active power filter control method has been developed as a result of the best possible performance for eliminating harmonic components from the voltage or current waveform. Usually, a traditional PI controller is used to manage voltage. However, an Artificial Neural Network (ANN) controller has been incorporated in this research effort due to its limitations, which include the time-consuming and challenging process of detecting PI parameters, among other downsides including the inability to increase the system's transient reaction. This is a result of the controller's quick recognition speed, capacity for learning, and versatility to work with any system.

A network of interconnected artificial neurons that use the connectionist method to compute information makes up an artificial neural network.

It shares two characteristics with the brain:

(i) The network acquires data through the process of learning.

(ii) Interneurons with stronger connections are used to store the data.

The extensive DC-link voltage data for the "n" and "n-1" intervals acquired using the conventional method is available in the MATLAB workspace.

Following that, the obtained data is used to train the ANN Controller.

The input and output layers have a fixed number of neurons to process the information. Every training session includes seven hidden layers with 1000 iterations and six validation tests to lower the probability of errors. In the case of SAPF, prompt and highly accurate identification of the disruptive signals and prompt processing of the reference signals are prerequisites for the planned compensation.

RESULTS AND DISCUSSIONS:

ANALYSIS OF DROOP MECHANISM

Normally droop is controlling the output voltage and frequency according to variation of load. So, without droop control system doesn't response. The output of mppt has two closed loop which is given to droop control. when frequency deviation is introduced into droop controller, then grid side frequency will drop and high voltage capacitor (C_2) will response and also system power will increase. With control of ANN controller to reduction the amplitude of capacitor voltage droop and system power. By plotting the waveforms of output voltage and output power is shown in figure 14 and 16.

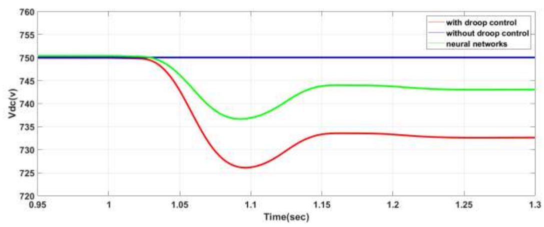

Fig.14. Influence of different parameter changes on Droop mechanism

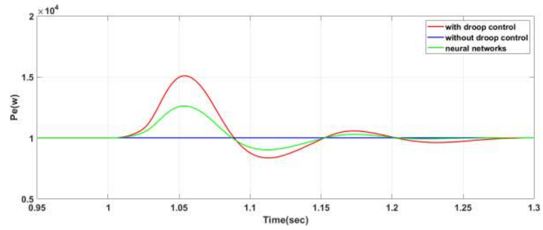

Fig.15. Influence of different parameter changes on Droop mechanism

ANALYSIS OF INERTIA

In a inertia analysis, proportional coefficient(K_p) and integral coefficient(K) keep constant and droop coefficient(D_p) only changing, then D_p decreases, 1/Dp increases, the oscillation amplitude of high voltage capacitor (C_2) increases i,e more capacitor voltage drop and system power is also increases. Different values of droop coefficient is shown in Figures 16 and 17 with the help of ANN controller to control or reduction the amplitude of capacitor voltage and output system power. In summary, the more $1/D_p$, inertia of system is more.

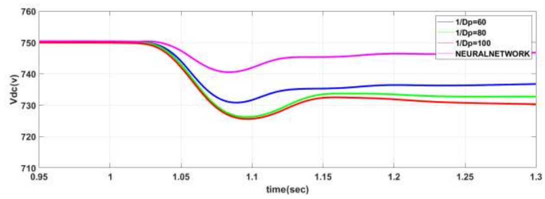

Fig.16. Influence of droop coefficient Dp on DC voltage

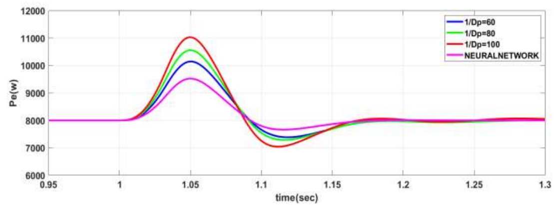

Fig.17. Influence of droop coefficient Dp on system power

ANALYSIS OF DAMPING

In a simulation of damping analysis, droop coefficient (D_p) and integral coefficient (k_i) keep constant and only changing the proportional coefficient (k_p), then the capacitor released is bigger. The low of capacitor (C_2) drop and low the amplitude of voltage and power, different values of proportional coefficient (k_p) is shown in Figure 18 and 19 with the help of ANN to reduction amplitude of the DC side capacitor voltage and output system power, which specifies that damping capacity of the system is stronger. In summary, higher the k_p and damping effect is higher.

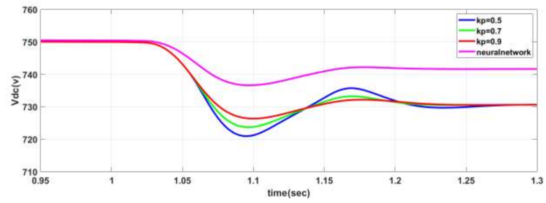

Fig.18. The Influence of P controller on DC voltage

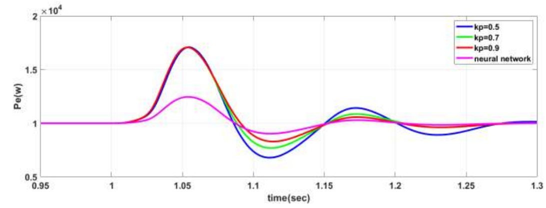

Fig.19. The Influence of P controller on system power

ANALYSIS OF SYNCHRONISATION

In a synchronization analysis, proportional coefficient (K_p) and droop coefficient (D_p) keep constant, only changing the integral coefficient (K_i). By increasing the the capacitor (C_2) voltage and power also increases. controlling the ANN to reduce the amplitude of the capacitor voltage and system power. Different values of integral impact as shown in Figure 20 and 21. In summary, more K_i the and synchronization effect also more.

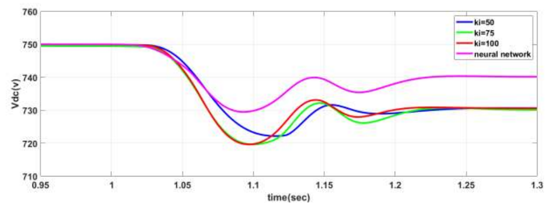

Fig.20. The Influence of I controller on DC voltage

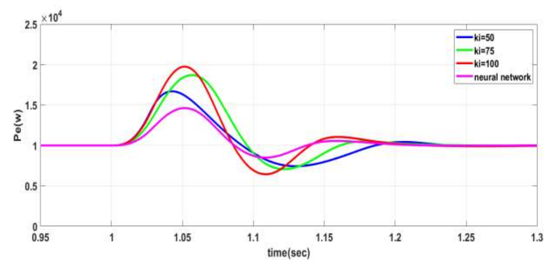

Fig.21. The Influence of I controller on system power

TABLE.1. Influence of different parameters change in system

	Voltage(volts)	Power(kw)
Without droop control	**750**	**10**
With droop control	**726**	**15**
Neural network	**736**	**12**

Above shows the final results of voltage and power without droop control, with droop control and neural network respectively.

TABLE.2. Droop coefficient (Dp changes)

	Voltage (volts)	Power (kw)
1/Dp=60	721	10.2
1/Dp=80	727	10.5
1/Dp=100	726	11
Nueral network	741	9.5

Above shows the final results of voltage and power with different droop coefficients (Dp change)

TABLE.3. Influence of P controller (Kp changes)

	Voltage(volts)	Power(kw)
Kp = 0.5	721	17
Kp = 0.7	724	17
Kp = 0.9	726	17
Neural netwok	737	12.5

Above shows the final results of voltage and power with different P controllers (Kp change)

TABLE.4. Influence of I controller (Ki changes)

	Voltage (volts)	Power(kw)
Ki = 50	722	17
Ki = 70	720	18
Ki = 100	719	19
Neural network	731	14.5

Above shows the final results of voltage and power with different I controllers (Ki changes).

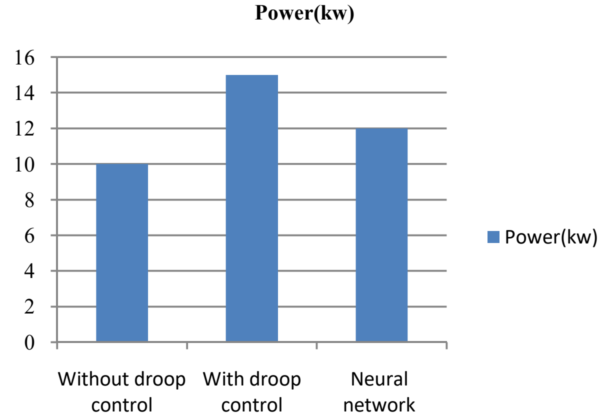

Fig.22. Influence of power change in Droop mechanism system

Above graph shows that, graphical representation of changes in power in **Droop mechanism system**

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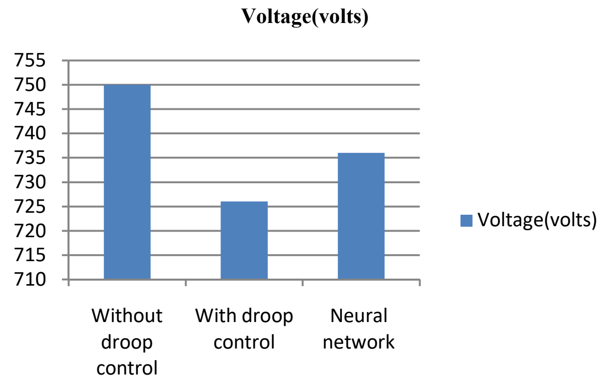

Fig.23. Influence of voltage change in Droop mechanism system

Above graph shows that, graphical representation of voltage change in Droop mechanism system

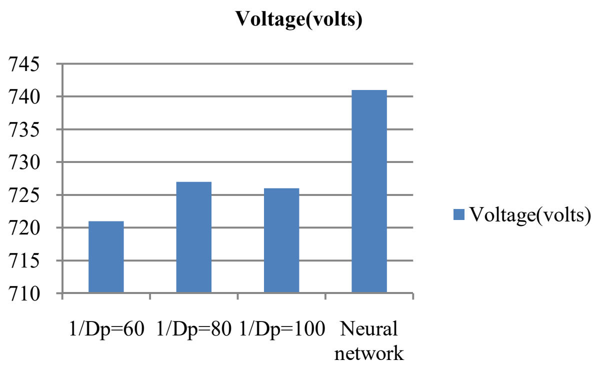

Fig.24. Influence of voltage change in inertia in system

Influence of voltage changes are shown in the above figure in inertia.

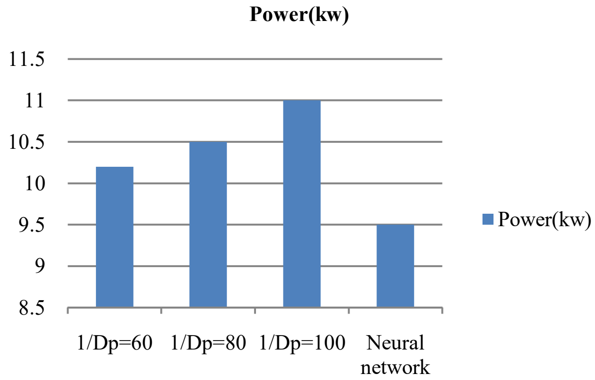

Fig.25. Influence of power change in inertia in system

Figure shows the graphical representation of power changes in inertia.

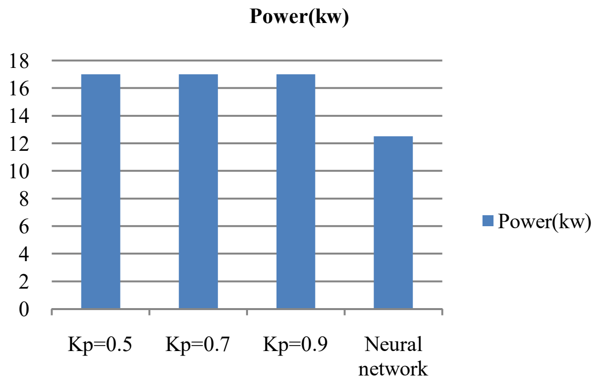

Fig.26. Influence of power change in damping in system

Figure shows the graphical representation of power changes in damping systems.

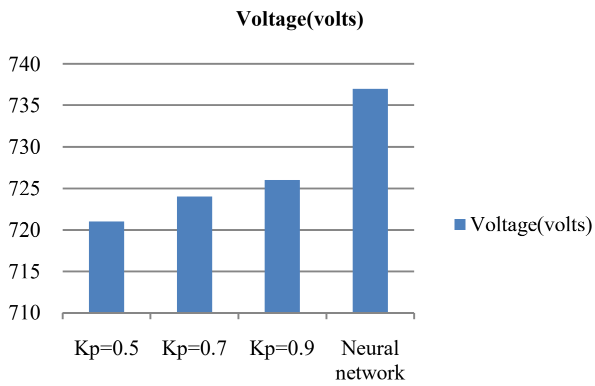

Fig.27. Influence of voltage change in damping in system

Above figure shows the voltage changes in damping system graphically

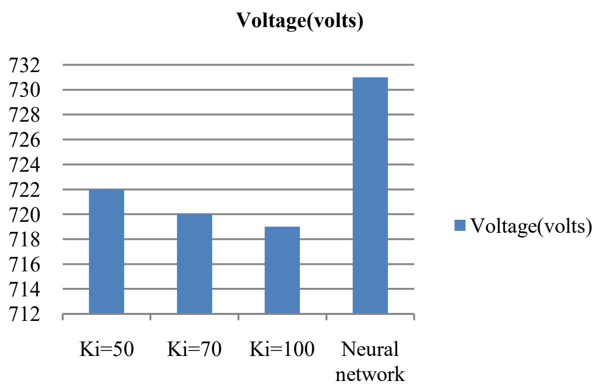

Fig.28. Influence of voltage change in synchronisation in system

Voltage changes are occurred in the synchronisation system are shown in above figure.

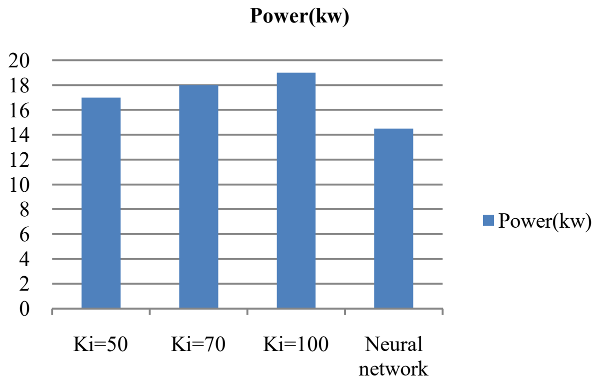

Fig.29. Influence of power changes in synchronisation in system

Figure shows the graphical representation of power changes in synchronisation system.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, the implementation of an Artificial Neural Network (ANN) controller topology in a Grid-Tied Photovoltaic (PV) Power Generation System with DC Voltage Droop Control represents a significant advancement in the field of renewable energy and grid integration The ANN-based controller has shown remarkable precision in regulating the DC voltage of the PV system. This precision ensures that the PV system consistently operates within the desired voltage range, maximizing energy production and improving grid integration. The integration of DC voltage droop control with an ANN offers a dynamic and adaptable solution for maintaining grid stability. This increased efficiency leads to higher energy yields, reducing dependence on conventional energy sources and promoting sustainability

The future scope for ANN controller topology in Grid-Tied Photovoltaic (PV) Power Generation Systems with DC Voltage Droop Control is promising, with numerous opportunities for further research, development, and implementation. Here are some hybrid energy systems, grid interactive micro grids and Integration of Energy Storage. So, we can prefer ANFIS based model for future scope to achieving better results.

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