MPPT Control of PV Grid with GOA Optimized Neural Network

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***Abstract* -** In this work we maximize the transmission power using the MPPT method. This aim is achieved by training a neural network with the help of MPPT dataset. An optimization algorithm called Grasshopper optimization algorithm (GOA) used to train the NN. GOA only trains the weights and biases of the NN. The testing will be performing on real time based simulation process. A simulation model is developed for the MPPT control PV array connected grid. We compare the results of GOA-NN based optimization with the PSO-NN based optimization simulink model. Our aim is to developed a MPPT control PV grid connect model with improved efficiency. GOA-NN based PV grid MPPT control provides the better results than the PSO-NN based.

***Keywords* -** MPPT, NN, GOA, ESS, PV Grid etc.

I. INTRODUCTION

The basic need for the improvement in the PV system control is modifying in the control which is further able to control the active and reactive power level on the point of base coupling with the grid. In the case of conventional PV system which uses the power electronic converters, the reactive power control methods are easy to implement, they can control the reactive power of the network. The actual amount of reactive power exchange through the PV system to the grid can be easily controlled in that case [4].

On the other side, the active power methods are not very simple for the conventional PV system. The active power control technique is the maximum power point tracking (MPPT) used to maximize the produced energy. Only two prospects are providing active power methods in terms of the PV system.

- In case of no optional point, the PV system can store the active power margin of the grid or
- Like an energy storage system (ESS) can serve as the support technologies

A. ESS in power system - In PV system some energy or power loss present in a higher degree. These losses can be avoided by install the Energy Storage System (ESS) at the dc or ac level of the power system. We can implement ESS as a centralized or decentralized solution to the PV system. The PV system injects the maximum energy due to the solutions and responds to the grid need while ESS is applicable. The cost of the PV system increased by ESS size. If the size of the ESS is large than the cost will be high; otherwise cost will be low with ESS has a small size.

B. Energy Management - Solar energy resources are fluctuating in nature; the main difficulty is that intermittent energy production with continuous energy demand. These types of difficulties can be removed by using the EMS in which RES technology with the PV system provided better stability to the network. But the cost of the overall network increased by using RES technology and short lifetime is the major challenge to the network. The optimization of the cost of the energy and their losses provided better results for future aspects.

C. Needs of PQ - To obtain a good smart grid system microgrid is the main components among them. Microgrid provides the flexibility to the system, integrating DER and storage system and also solves the problems related to the PQ. According to the new definition of DG in terms of PV system new problems have arrives in PQ.

According to the previous study following objectives are considered for the research

- To design a MicroGrid system with PV connection and ESS equipment
- To enhance the performance of the PV system network by using the MPPT scheme and optimize the parameter with GOA optimize NN.
- Compare the result with PSO optimize NN.

II. RELATED WORK

Various methods were proposed for the maximization of transmission energy in the power system. The multiple DG sets were implemented to the microgrid which improves its efficiency [1]. The energy can be saved by the home energy management scheme [2] with BIPV and motorized blinder. The constant power production can be used for the PV system analysis [3]. The peak shaving methods provided to the grid connected system which increases the production of the electricity [6].

The power electronic devices like STATCOM, UPFC, and SVC used in the power system. These devices maximize the energy of the grid. There are lots of study involve the PE devices as energy saver [7-13].

The maximum power point tracking (MPPT) improve the performance of the PV grid integration system. The digital control MPPT used in the modification of the perturb algorithm which provided some advantages to the PV system. The main advantage of the PV system using the MPPT was accuracy improvement, and control functions operate very smoothly. Due to the fast dynamic response of the MPPT, the speed of the PV system power generation increased.

III. GOA OPTIMIZATION

The Grasshopper optimization is the nature inspired algorithm. It is used for the multi objectives solution. The nature inspired optimization algorithms deals with the two classes called exploration and exploitation. Basically grasshopper is the insect. Due to their destroy nature towards the crop and agriculture fields they considered as pest.

Figure 1: Real Grasshoppers and their life cycle [43]

Figure 1 shows the lifecycle of the grasshopper which carry the three stages mainly. Usually the grasshopper found individual but they join one of the biggest swarm of all the creatures. Grasshopper swarms are the nightmare for the farmers and their size may be of continental scale. One unique features of the grasshopper swarm is the swarming nature during the both stages nymph and adult [43]. Generally most of the grasshopper in nymph stage jump and move like the rolling cylinders. During their path, they eat entire vegetation. After this stage when they become adult, they construct swarm in the air and easily shifted to the large distance.

The algorithm inspired by two characteristics which discussed earlier exploration and exploitation. In terms of exploration the search agents are force to move abruptly and tend to move locally in exploitation. The mathematical model observation can prove the nature inspired optimization algorithm. The swarming behavior of the grasshopper represented by mathematical equation 1

$$X_i = S_i + G_i + A_i \quad (1)$$

The ith position of grasshopper represented by X_i, the gravity force reflected as G_i for the ith grasshopper, A_i and S_i shows the wind advection and social interaction. Above equation 1 can be written as the modification through the random number

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (2)$$

here $\boldsymbol{r_1}, \boldsymbol{r_2}$and $\boldsymbol{r_3}$ are taken as a randome number between the value 0 and 1. The calculation of social interaction is

$$S_i = \sum_{\substack{j=1 \\ j\neq 1}}^{N} s(d_{ij})\widehat{d_{ij}} \quad (3)$$

In equation 3 d_{ij} is the distance across the ith and jth position of the grasshopper which formulated as $d_{ij} = |X_j - X_i|$, s define as the strength of the forces, $\widehat{d_{ij}}$ is the unit vector from the ith and jth position of the grasshopper

$$\widehat{d_{ij}} = \frac{x_j - x_i}{d_{ij}} \quad (4)$$

$$s = f e^{\frac{-r}{l}} - e^{-r} \quad (5)$$

Equation 5 shows the social forces, where l the attractive length scale is and f is the intensity of attraction.

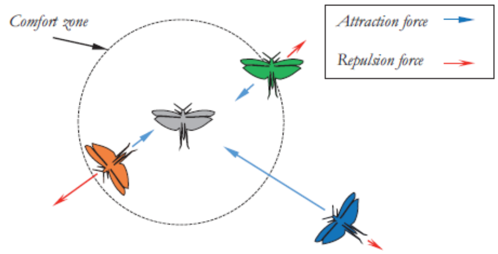

Figure 2: conceptual model of grasshopper comfort zone using the social force [43]

Figure 2 shows the conceptual model of the behavior of grasshopper as per their comfort zone based on social forces. The function of social forces also divides the space across two grasshoppers as a comfort zone, attraction zone, and the repulsion region. The strong forces are not applied by this function in the large distance grasshoppers. The mapped distance of grasshoppers modifies this limitation into some interval.

The gravity force can be calculated as

$$G_i = -g\widehat{e_g} \quad (6)$$

In equation 6 g and $\widehat{e_g}$ are the gravitational constant and unity vector towards the length of the earth. The estimation of wind advection as per equation 7

$$A_i = u\widehat{e_w} \quad (7)$$

u Represent the constant drift and $\widehat{e_w}$ reflects the direction of the wind in unity nature. The nymph stage grasshopper has no wings their movement depends on the direction of the wind. By putting the values of all the parameters in to the equation 1

$$X_i = \sum_{\substack{j=1 \\ j\neq 1}}^{N} s(|X_j - X_i|)\frac{x_j - x_i}{d_{ij}} - - g\widehat{e_g} + u\widehat{e_w} \quad (8)$$

In equation 8 N is the number of the grasshopper and s value calculated from equation 5. Therefore the equation 8 shows the position of the nymph stage grasshopper; we cannot implement these equations in to the optimization process and simulation.

The position of grasshopper update as per equation 9 due to the reason that grasshopper comes into stable condition very fastly and specific converge point is not achieved by swarm. The equation is

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j\neq 1}}^{N} c\frac{ud_b - id_b}{2} s(|X_j^d - X_i^d|)\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \quad (9)$$

Finally, the position of the grasshopper update as shown in equation 9. ud_b and id_b are upper and lower limit in the Dth dimension, $s(r) = fe^{\frac{-r}{l}} - e^{-r}$, $\widehat{T_d}$ reflect best optimal solution of the problem, the stable, attraction and repulsion region are minimized by the decreasing coefficients c. The next position of the grasshopper depends on the previous position of grasshoppers.

The first term of equation 9 reflects the position of the present grasshopper with respect to reference grasshopper. Based on the global position, current position, and other search agent position, the optimal position of the grasshopper is updated by the GOA.

IV. PROPOSED WORK

In this work we used neural network initially to track the maximum power generated form PV array and then NN is updated with optimization method which is grasshopper optimization algorithm (GOA). Previously particle swarm optimization (PSO) was used for this purpose. Optimization process changes the input weights and biases values of NN to achieve less error. Neural Network (NN) is also an iterative process which updates its input weights and biases to obtain minimum MSE (Mean Square Error). The feedback propagation loop provides by using lqenberg algorithm. But this algorithm only iterates locally which causes not cover all the minima points by lqenberg algorithm. The Mean Square Error may be reduces due to skip section of input weights and biases. This problem can be removed by the optimization process. We use Grasshopper Optimization Algorithm (GOA) which discussed in previous chapter for the tuning of NN parameters. The output of the NN obtained by using the formulation

$$output = input * IW_i + B_i \qquad (10)$$

In above equation IW_i are the weights of the input, and B_i are the biases. Both parameters input weights and biases depend on the number of hidden layers. We use GOA algorithm to tune the values of input weights and biases.

A complete stepwise algorithm explain below

Step1. Load the MPPT pre generated IN/OP data and divide complete data 70:30 ratio for the testing and training process of neural network.

Step2. Formulate or generate the neural network script in MTALAB to form and train the system on the basis of weights and biases which optimized in the next step.

Step3. Initialize the GOA parameters like X_i and C. The number of iterations and search agents also initialize in GOA. Further pass the NN generated script through the GOA and obtained the dimensions of weights and biases.

Step4. The initialize inputs from the NN network provided to the GOA optimization. It can be taken as random values.

Step5. Update the neural network weights and biases by calling the objective function. Estimate the Mean Square Error (MSE) for the updated values of the testing dataset.

Step6. The randomized position of the search agents updated as estimate in equation, distance equation among grasshoppers, and social interaction calculated as per equation 3, 4 and 5.

All the used parameters are explained in chapter 3. Some other calculations are provided in chapter 3 which update the parameters of the GOA.

Step7. The latest position obtained using the formula

$$X_i = S_i + G_i + A_i$$

And modify the equation 1 as per 8 and 9

Step8. After update the position of the search agent call again the objective function and store the latest value of MSE.

Step9. Select the values of weights and biases by which the low MSE value estimated. These values further used for the improvement.

Step10. This process will continue until all the iterations finished.

Step11.Finally minimum value of Mean Square Error (MSE) is obtained by update values of weights and biases of the NN.

V. RESULTS AND DISCUSSION

In this work we used Grasshopper Optimization algorithm (GOA) to tune the parameters of the neural network (NN). The weights and biases of NN are optimized by GOA then estimate the minimum MSE to obtain the duty cycle for MPPT. All the script related to the GOA and NN developed in the MTLAB software. MATLAB provided the better user interface among all the scripts.

The neural network trained with the help of weights and biases then optimize the parameters of NN with GOA method. The results compared with the PSO base NN network. Figure 3 shows the NN trained network in which 1 hidden layer created the 10 neurons.

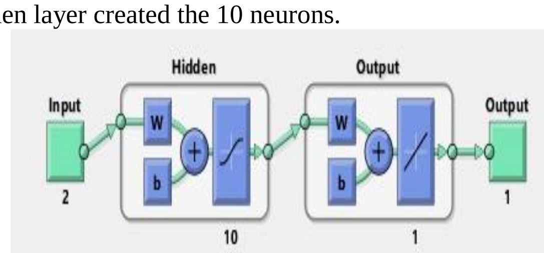

Figure 3: NN trained network

This neural network optimized with the proposed method GOA and previous method PSO. Both the work arrives in the categories of optimization and their analysis is provided between the number of iterations and final best value of the solution of the fitness function.

The optimization curve must be decreasing for initial iterations and must settle down to a minimum fixed MSE for after little iteration. As soon as it settles, better is the optimization. In our comparison case, GOA is settled down to lower value than PSO tuned NN, so it confirms that GOA performs better than PSO. A comparison of PSO and GOA optimization for our work shown in the figure 4

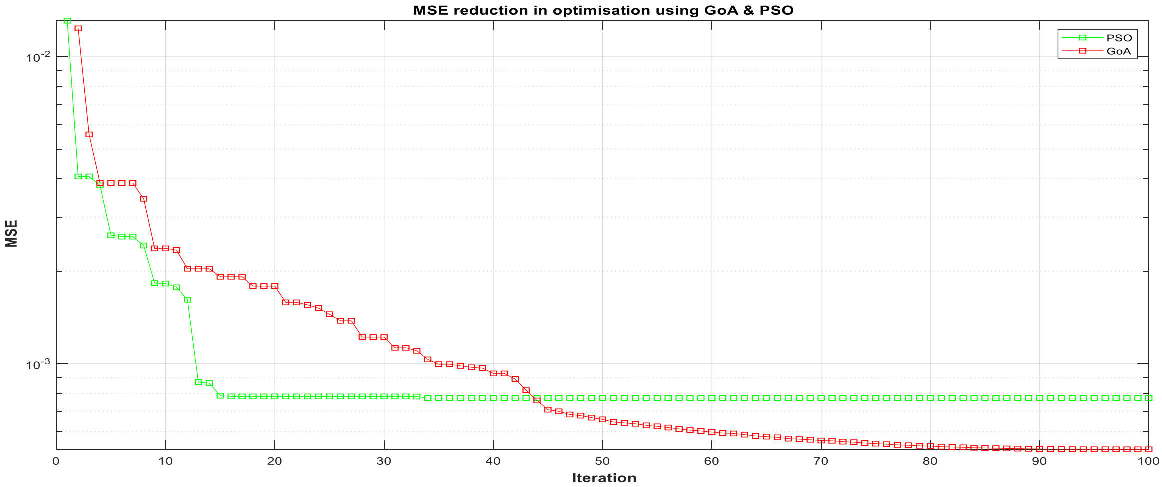

Figure 4: GOA-NN and PSO-NN comparison on MSE estimation for the MPPT control

The MATLAB simulink model developed as grid connected PV array is shown in figure 5 and 6. The neural network app of MATLAB also facilitates to deploy the trained NN model as simulink model.

After training of NN on the collected data of 25000 samples, we tested it with another 10000 set of sample values of input (temperature and irradiance). The tested data is plotted in figure 7.

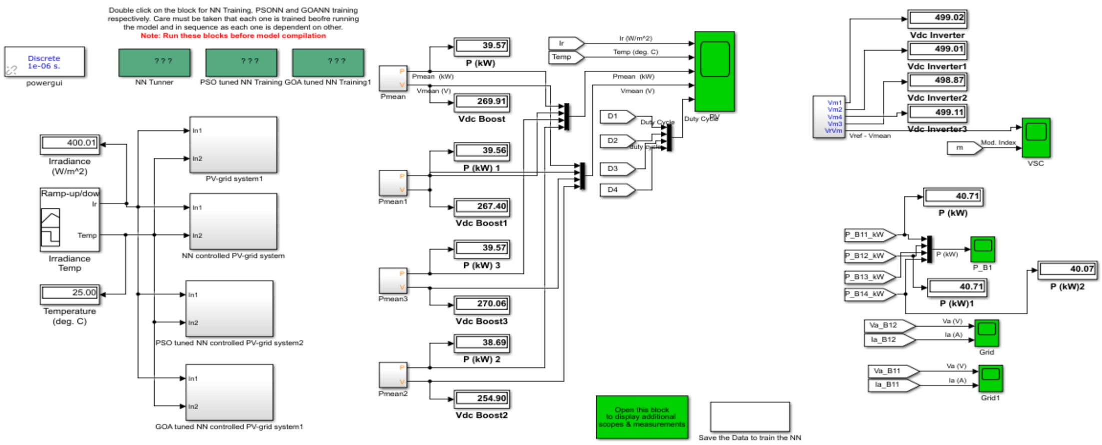

Figure 5:. Main simulink model for comparison of I&C PV grid, NN tuned PV grid, PSO-NN tuned PV grid, GOA-NN tuned PV grid

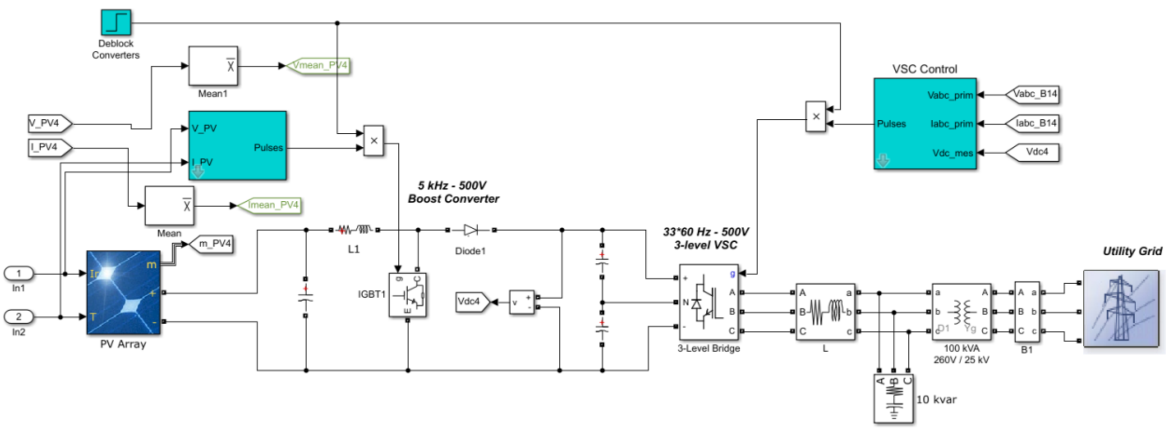

Figure 6: Grid connected PV array model simulink model for which MPPT controller is tuned

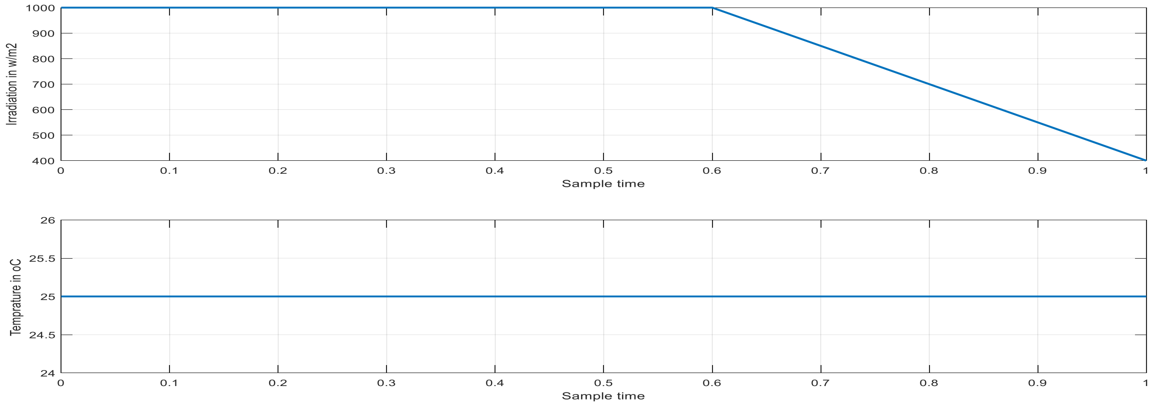

Figure 7: Input temperature and varying irradiation under test

We compared the output power of PV array after MPPT controlled by I&C, LM neural network, PSO tuned NN and GOA tuned NN, plotted in figure 8.

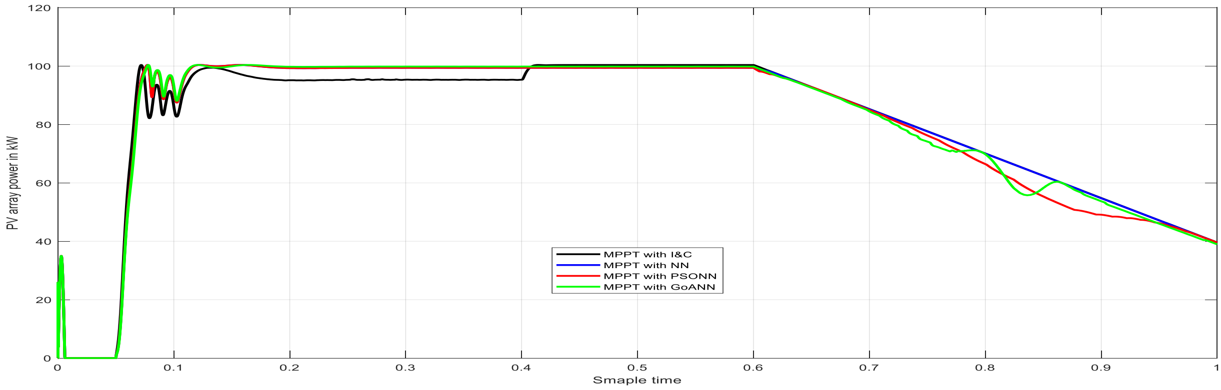

Figure 8 PV array output after MMPT control by four methods including proposed GOA tuned NN

The graph clearly demonstrates that the GOA tuned neural network weights and biases are controlling duty cycle to achieve maximum power among all these methods. Similarly the PV array voltage is also enhanced most by proposed optimization for NN as shown in figure 9. The input irradiance decreases at 0.6 sec which also results in fluctuation of PV array voltage but our proposed method still manage to have maximum constant voltage at the output. It shows proposed MPPT method is far better than previous used by tuning the NN weights and biases by GOA optimization.

Finally the duty cycle, which is the output of neural network is shown in figure 10 for all four cases. We can't specify by just analyzing the duty cycle graph that which will give better results but if we connect the variation in duty cycle with variation in PV output voltage then a pattern can be noticed

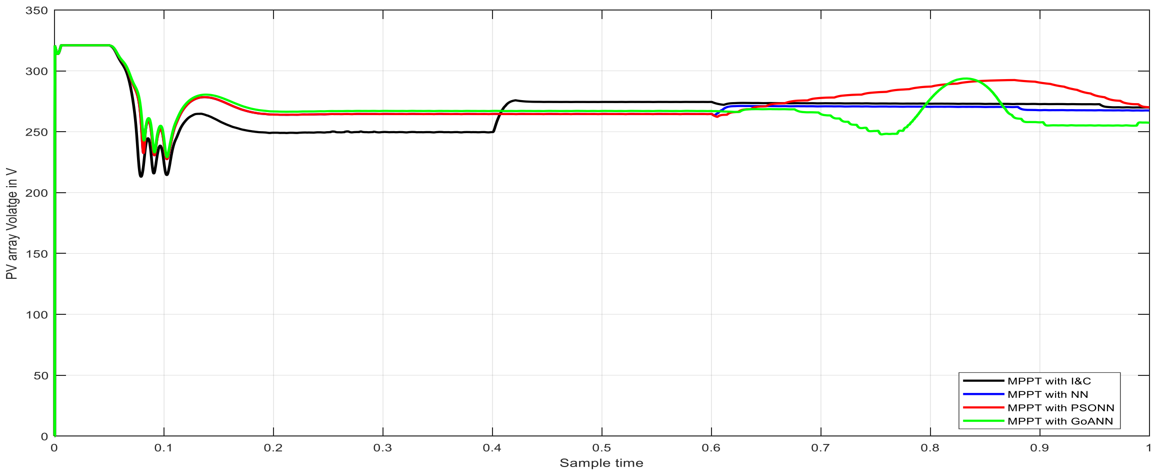

Figure 9: PV array Voltage comparison of MPPT method using I&C, NN, PSONN and GOANN

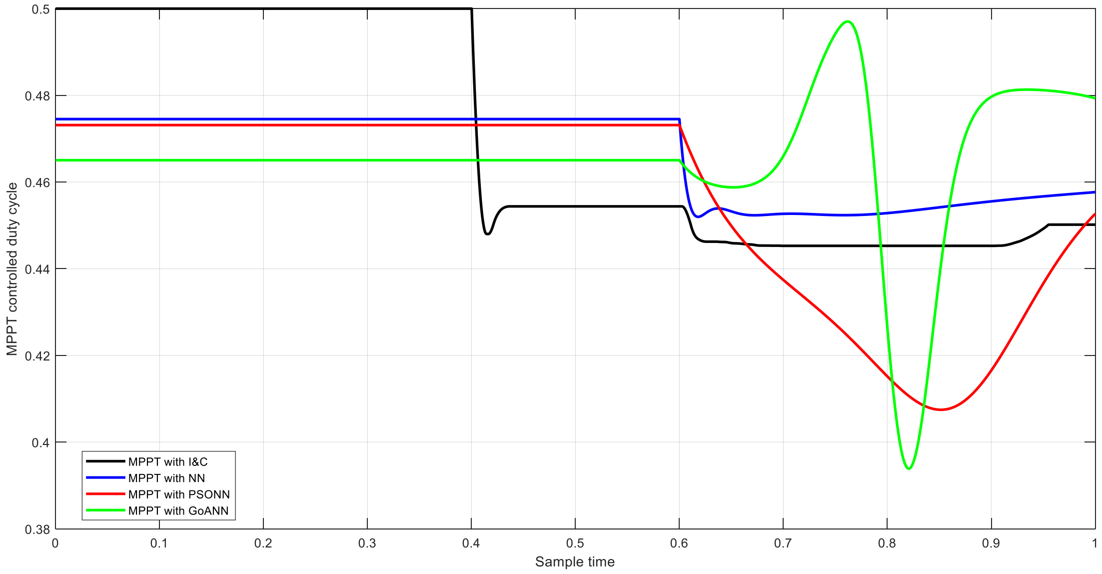

Figure 10: Duty cycle comparison of MPPT method using I&C, NN, PSONN and GOANN

The MPPT controller boosts the transmitted power to grid but a point of common coupling DC voltage has to maintained constant which shows both plants are in synchronization. We used a VSC controller for that which maintains the DC at common point of coupling. The DC by all four methods is shown in figure 11 which is constant for every methods that means no one disturbs the synchronization of system.

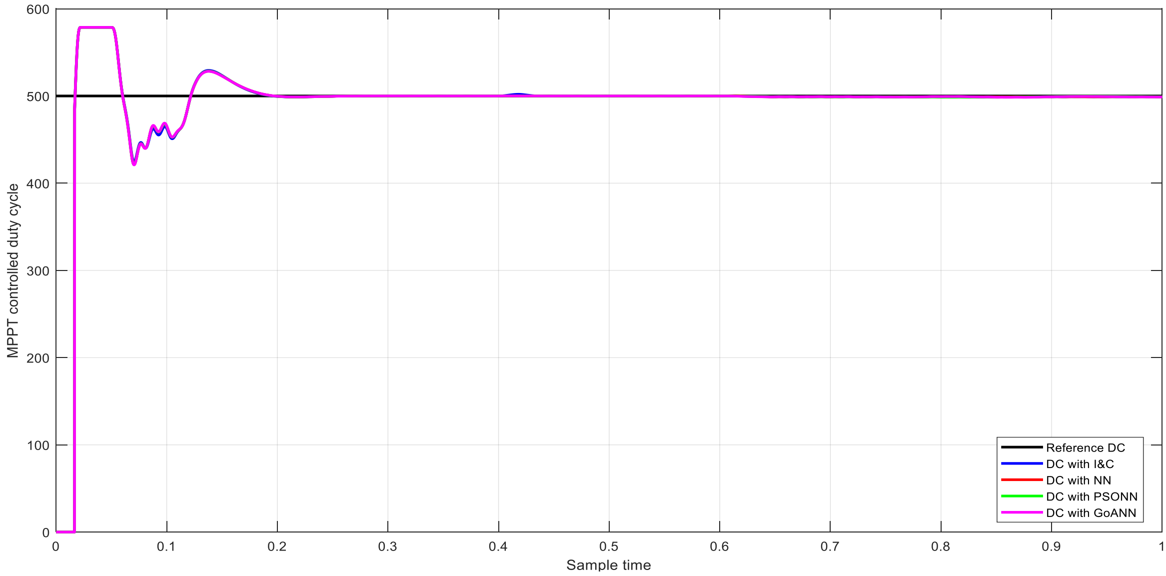

Figure 11: DC voltage at point of common coupling

VI. CONCLUSION

In this work we implement the MPPT scheme to increase the power transmission system from PV array to grid with a neural network fraud identification method. NN is inspired by the brain activity like pattern recognition and associative memory. The main feature of neural network is that it recognizes similar pattern, predictive the future values based upon the memory of the pattern. We developed a PV array grid connected model with the MPPT control. The efficiency of the PV grid increase with the help of NN and optimization. The parameters of NN (weights and biases) are optimized by GOA (Grasshopper Optimization Algorithm). The neural network optimize with the GOA which helps to improve the MSE. The comparison among the local based optimization like PSO also performs with the global based optimization GOA. GOA provided the better results than the PSO. It means the MSE estimation through the GOANN network is minimum so the highest maximum power obtained from the PV array system.

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