Development of a Photovoltaic MPPT Control based on Neural Network

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***Abstract*—The Maximum Power Point Tracking (MPPT) is an important factor to increase the efficiency of the solar photovoltaic (PV) system. This paper presents a solar PV system containing a solar PV array, a DC/DC boost converter and a load. Different MPPT algorithms have been established with their features. The conventional algorithms (Perturb and Observe, Incremental Conductance and Open Circuit Voltage) show a lot of drawbacks. The major issue is the tracking of the Maximum Power Point (MPP) when environmental conditions change faster. So, a MPPT technique based on Neural Network (NN) was developed and which can enhance the efficiency and gathers the advantages of a lot of techniques. A multi layer neural network with back-propagation algorithm is used in order to have a small Mean Squared Error (MSE). The inputs of NN are irradiance, temperature and the output is the duty cycle that controls the boost converter. Finally, it is discussed the results and made comparison in terms of performance of the different algorithms, covering the overshoot, time response, oscillation and stability.**

***Index Terms*—Maximum Power Point Tracking algorithms, Neural Network, DC/DC boost converter, Solar PV system.**

I. Introduction

The energy consumption is growing in all regions of the world due to demographic development and industrialization. Currently, most of the production of electrical energy is based on non-renewable resources like coal, natural gas and oil, and those energy resources have harmful consequences on the environment.

The solar photovoltaic (PV) system is the more efficient over the other renewable energy sources [1]. The solar energy has many applications and it is the most available energy, becoming more flexible and that is why it is more useful. When the solar PV panel is directly connected to the load (direct connection) the operating point depends on the intersection between the current vs voltage (IV) characteristic and the load [2], as shown in Fig. 1. For the operating points A, B and C, the output power of solar PV panel is respectively P_A, P_B and P_C. Both of P_B, P_C are lower than the maximum power P_A, the transmission of the maximum power is not available. Different equipment must be connected with the photovoltaic generator to ensure the optimum transfer of energy to the load. The power generated depends on temperature, irradiance and also the load.

So, to make the photovoltaic generator works in its maximum power we use a Maximum Power Point Tracking (MPPT) algorithm. A lot of them are presented in literature. The most popular algorithm is Perturb and Observe (P&O) which is based on the perturbation of the solar PV voltage and observing the output power if it increases or decreases [3]. This perturbation can presents power losses and oscillation around the Maximum Power Point (MPP). The Incremental Conductance (IncCond) method shows that the slope of the solar PV characteristic is zero in the MPP, positive on the left of the MPP, and negative on the right [4]. This method requires high accuracy control and sensors. The open circuit voltage (OCV) method reaches the MPP by the relationship between open circuit voltage and the voltage at MPP. It is economical and simple but, presents a lot of power losses [5]. Those three MPPT algorithms with a lager step size have a quick response. But, suffer from the high oscillation in the steady state. On the contrary, with a smaller step size the converging speed is low. But, high accuracy presented in the steady state. For this reason, in [6] a MPPT algorithm is proposed based on two stages: (1) the computing stage and (2) the regulating stage. The first stage provides an initial duty cycle based on the (IV) characteristic and DC/DC converter. The second stage adjust the duty cycle by using a small step size. The proposed Neural Network (NN) algorithm generates the duty cycle in one stage with high speed response in small time. Also, another MPPT intelligent methods have been developed such as fuzzy logic methods

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[7], T–S fuzzy method [8] and genetic algorithm methods [9]. In addition, NN algorithm can generate voltage or current. In case when the output is current or voltage, the output generated is used as a reference to the control unit as presented in [10]. In this paper a NN algorithm is proposed to track the MPPT and compare the obtained results with the conventional algorithms. The network is developed after many training by adjusting the weights using a back-propagation algorithm.

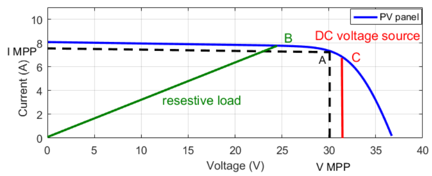

Fig. 1. The operating point of the solar PV panel according to the load in the direct connection.

II. Modeling of a photovoltaic cell

To develop a precise equivalent circuit for a solar PV cell, it's necessary to understand the physical configuration of the elements as well as the electrical characteristics of each element. Many mathematical models have been proposed to represent the solar PV cell. The "one-diode model" which based on modeling the solar PV cell by one diode, the "two-diode model" and the "polynomial model" [11]. The simplest circuit model is the "one-diode model" consisting of an i_{ph} current generator which is directly dependent on the solar irradiance (it varies proportionally with the incident radiation) [12]. The Fig. 2 shows the one diode model for the solar PV cell.

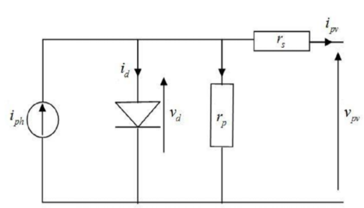

Fig. 2. The one diode model for the solar PV cell.

Being,
i_{PV}: the solar PV cell current [A].
v_{PV}: the solar PV cell voltage [V].
i_{ph}: the photo-current [A].
r_S: the series resistor [Ω].
r_P: the parallel resistor [Ω].
i_d: the current across the diode[A].
v_d: the diode voltage[V].
The expression of the photovoltaic current is given by:

$$\begin{aligned} ipv &= iph - id - ip \\ &= iph - is[e^{\frac{q*(v_{PV}+i_{PV}*r_S)}{(n*K*T)}} - 1] - \frac{v_{PV}+i_{PV}*r_S}{r_P} \end{aligned} \quad (1)$$

Being,
q: electron charge $(1.6 * 10^{-19}$ [C]).
n: the ideality factor of the diode.
K: Boltzmann's constant $(1.38 * 10^{-23}$[JK]).
T: operating temperature [K].
i_p: the current across the parallel resistor [A].
i_s: diode saturation current [A].

III. MPPT algorithms

A. Perturb and Observe

The P&O method is the most popular MPPT algorithm due to its simplicity [13]. It's one of the hill climbing algorithms. The objective of this algorithm is to operate the system at it's maximum power by incrementing or decrementing the voltage at the operating point and observing the effect of this perturbation on the power, as is represented in the flow chart in Fig. 3.

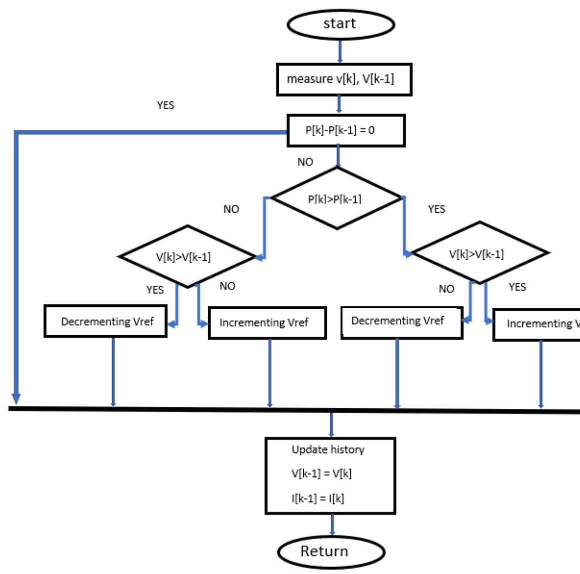

Fig. 3. The flow chart of P&O method.

B. Incremental Conductance

Incremental Conductance is also one the hill climbing techniques. Where, the MPPT command tries to raise the operating point of the solar PV generator along the solar PV characteristic until it reaches MPP [14]. It based on the principle that the slope of the solar PV array power curve is zero at the MPP($\frac{dP}{dv} = 0$) . It searches for MPP based on equality of conductance (G=$\frac{I}{V}$) and conductance increment (G=$\frac{\Delta I}{\Delta V}$).

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = I\frac{dV}{dV} + V\frac{dI}{dV} = I + V\frac{dI}{dV} \approx V\frac{\Delta I}{\Delta V} + I \quad (2)$$

Where,

$$\begin{cases} \frac{\Delta I}{\Delta V} = -\frac{I}{V} & if \quad P = MPP \\ \frac{\Delta I}{\Delta V} < -\frac{I}{V} & if \quad P \quad in \quad right \quad of \quad MPP \\ \frac{\Delta I}{\Delta V} > -\frac{I}{V} & if \quad P \quad in \quad left \quad of \quad MPP \end{cases} \quad (3)$$

This algorithm flow chart is shown in Fig. 4.

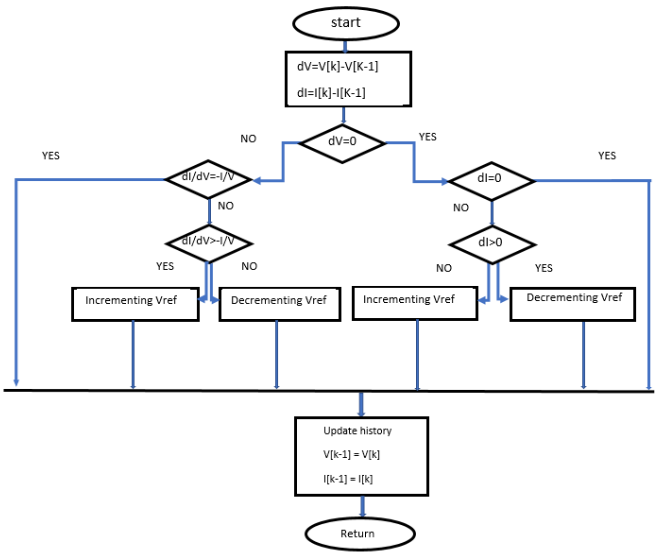

Fig. 4. The flow chart of IncCond method.

C. The open circuit voltage method

The open circuit voltage method achieves MPP based on the open circuit voltage (V_{OC}), such that the voltage at MPP (V_{MPP}) is around 70% to 80% of the solar PV open-circuit voltage [15] ($K = \frac{V_{MPP}}{V_{OC}}$)(from 70 % to 80 %). This method is characterized by only the solar PV voltage is necessary to be measured, and a simple control loop can reach the MPP [16], the flow chart of OCV method is shown in Fig. 5.

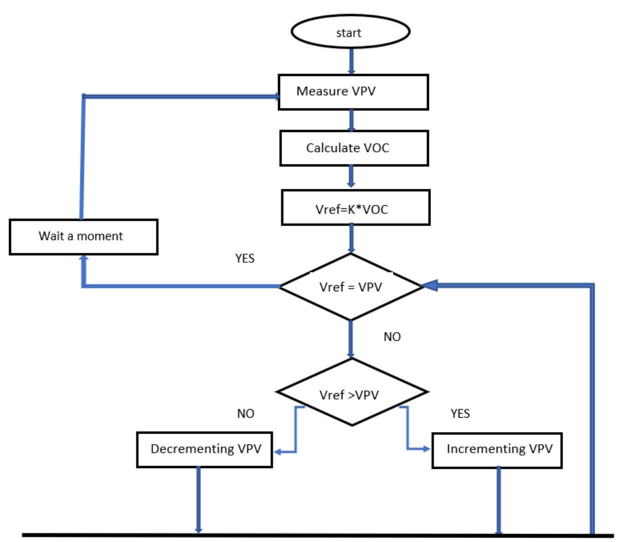

Fig. 5. The flow chart of open circuit voltage method.

D. The proposed MPPT algorithm based on Neural Network

In the way of improving the performances of the MPPT, one of the modern MPPT techniques is the Neural Network algorithm which is inspired from the biological nervous systems. Every single connection between two neurons has a weight which is used to adjust the network, i.e, change the weights until the outputs achieve the targets [17]. The inputs of the NN are the temperature and irradiance. The target is the duty cycle of the boost converter as shown in Fig. 6.

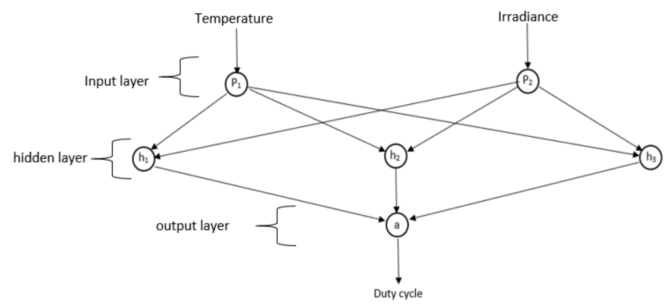

Fig. 6. The NN mechanism.

The validation of the network justified by the output's convergence to the target i.e, a small MSE [18].

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(t_i - a_i)^2 \quad (4)$$

Where,
N: the number of outputs.
t: target.
a: the output.
The reduction of MSE obtained by adjusting the weights. So, the needs of back-propagation algorithm.

IV. System architecture and characteristics

The system architecture is the solar PV array connected to the load through a boost converter. A MPPT algorithm controls the switch to assure the functionality at the maximum power point. The Fig. 7 indicates the architecture of the system.

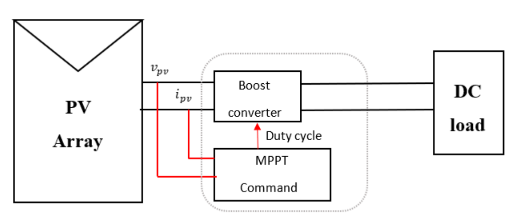

Fig. 7. The system architecture.

A. The solar PV array

The solar PV panel converts the energy that comes from the sun to electric energy. The modules can be connected to each other in series and/or parallel to form solar PV array. The specification of the solar PV array is token from MATLAB/SIMULINK platform which given in Table I.

TABLE I
THE SPECIFICATION OF THE SOLAR PV ARRAY.

Module	Aavid ASMS-220P
Maximum Power (W)	220.5
Cells per module (Ncell)	60
Open circuit voltage Voc (V)	36.8
Short-circuit current Isc (A)	8.08
Voltage at MPP Vmp (V)	30
Current at MPP Imp (A)	7.35
Temperature coefficient of Voc (%/deg.C)	-0.33641
Temperature coefficient of Isc (%/deg.C)	0.038465
Parallel strings	3
Series-connected modules per string	4

B. The boost converter

The boost converter used is a power converter with a DC output voltage higher than its DC input voltage. It contains two semiconductors (diode, switch) and at least one energy storage element. DC/DC converter is used to transfer the power from the solar PV panel to the load assuring the optimum transfer of the power. The switch is controlled through the MPPT algorithm with variable duty cycle according to the the temperature, irradiance and the load. The output capacity is added to reduce output voltage ripple. Also, the boost converter is called a step-up converter. The Fig. 8 indicates the boost converter structure.

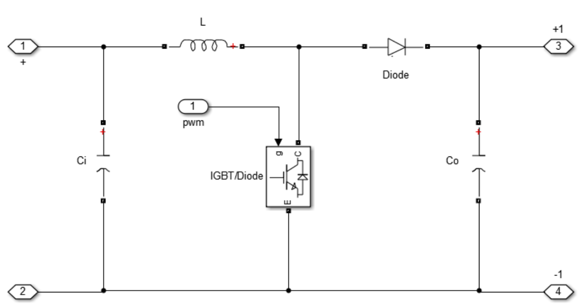

Fig. 8. The boost converter structure.

The design of the boost converter inductance depends essentially in the current ripple of the inductance which is inversely proportional to the inductance value [19]. The expression of the inductance is given by:

$$L = \frac{V_i * D}{\Delta i_L * f_{sw}} \tag{5}$$

Being,
D: the duty cycle.
V_i: the input voltage [V].
Δi_L: the current ripple of the inductance [A].
f_{sw}: the switching frequency [Hz].

The input capacitance was chosen according to the maximum power point voltage ripple factor in the standard test conditions (STC) [19]. The expression of the input capacitance is given by:

$$C_i = \frac{D}{8 * L * \Delta V_{MPP} * f_{sw}^2} \tag{6}$$

Being,
C_i: the input capacitance [F].
ΔV_{MPP}: the maximum power point voltage ripple factor [V].

The output capacitance depends essentially on the output voltage ripple factor as shown in eq. 7.

$$C_o = \frac{D * (1 - D)^2}{R_{mpp} * \Delta V_o * f_{sw}} \tag{7}$$

Where,
C_o: the output capacitance [F].
R_{MPP}: the maximum power point resistor [Ω].
ΔV_o: the output voltage ripple factor [V].

The Table II shows the boost's characteristics.

TABLE II
THE CHARACTERISTIC OF BOOST CONVERTER.

The input capacitance C_i	$3 * 10^{-5}$ F
Inductance L	$2 * 10^{-3}$ H
The output capacitance C_o	$5 * 10^{-4}$ F
Switching frequency	5 kHz
Resistance	72 Ω

V. THE SIMULATION RESULTS AND DISCUSSION

The OCV, P&O and IncCond algorithms are simulated with the same duty cycle step (ΔD =1.25*10^{-5}). The sample time of simulation is $T_s = 5 * 10^{-6}$s. For all the simulation results the system is the same, the only changing is in the MPPT algorithm as shown in Fig. 9.

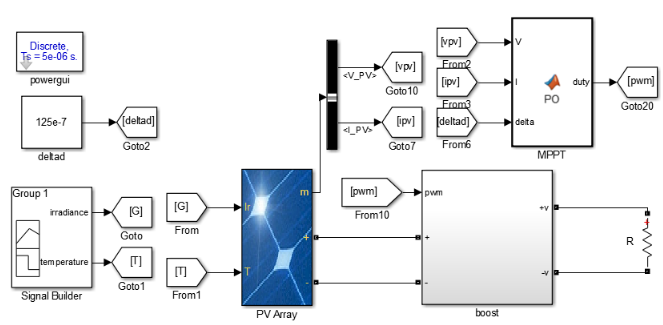

Fig. 9. The system's structure in MATLAB/SIMULINK.

The proposed multi layer Neural Network algorithm is trained using "nntool" in MATLAB. The feed-forward network with a back-propagation algorithm assures the adjusting of weights which is determined at the offline training.

The characteristic of the network is shown in Table III.

TABLE III
THE CHARACTERISTIC OF THE NETWORK.

Type of network	Feed-forward
Hidden Layer activation function	Sigmoid
Output Layer activation function	Linear
Back-propagation algorithm	Levenberg-Marquardt
Performance	Mean Squared Error (MSE)
Number of hidden neurons	5
Number of samples used in offline training	625

The samples are obtained by varying the temperature from $5°C$ to $45°C$ and irradiance from 100 W/m^2 to 1100 W/m^2. Some data are used to test and validate the network after training. The Fig. 10 presents a small Mean Squared Error (MSE), i.e, the network is well trained, the best MSE obtained is 4.2046*10^{-5} at epoch 77.

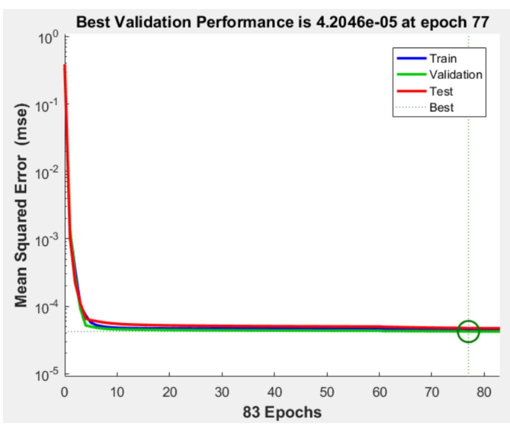

Fig. 10. The Mean Squared Error (MSE) of the NN.

The simulation results for the MPPT algorithms has been established under different conditions to see the response of each one.

Table IV shows the variation of the environmental conditions.

TABLE IV
THE VARIATION OF THE ENVIRONMENTAL CONDITIONS.

time (s)	0-1	1-2	2-3	3-4	4-5
Irradiance (W/m^2)	1000	1100	800	400	700
Temperature (C°)	25	45	35	5	33

The Fig. 11 shows that the data fall along a 45 degree line (R=0.99≈ 1), where the network outputs are equal to the targets.

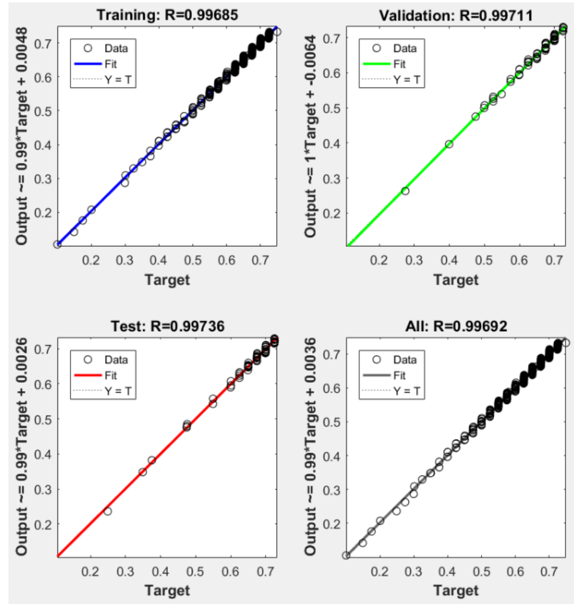

Fig. 11. The targets convergence.

It is observed from Fig. 11 that all the samples are aligned on the same line which represent a high accuracy of the acquisition of data and the validity of them.

The four MPPT algorithms are plotted in the same figure in order to compare them and to see the behaviour of each algorithm in a different temperatures and irradiances especially in the fast changing. The meteorologic conditions used are shown in the Table IV.

The Fig. 12 shows the output power consumed by the load using the four MPPT algorithms.

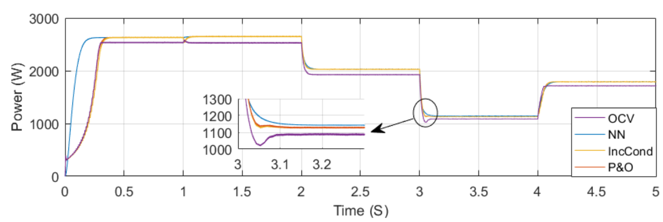

Fig. 12. The output power of the different MPPT algorithms.

The Fig. 13 presents the voltage over the load with the different MPPT algorithms.

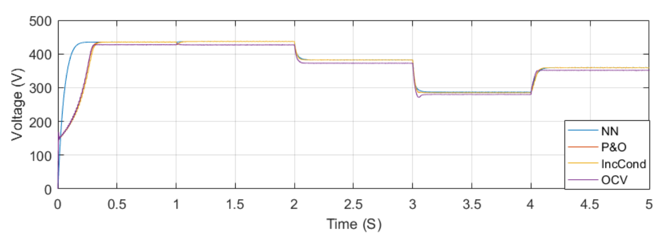

Fig. 13. The output voltage of the different MPPT algorithms.

The Fig. 14 indicates the duty cycle of the different MPPT algorithms.

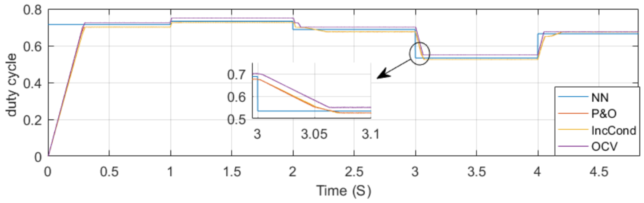

Fig. 14. The duty cycle of the different MPPT algorithms.

According to the Fig. 12, Fig. 13 and Fig. 14, the NN algorithm has quick response, i.e, it requires less time to reach the MPP and high efficiency and less oscillation comparing with the conventional methods. The OCV has also relatively short response time comparing with *P&O* and IncCond but, less output power. *P&O* has a high output power but, presents an oscillation around MPP. Also, IncCond has high output power but takes more time to reach the MPP.

In the rapidly changing of irradiance *P&O*, OCV, and IncCond present an overshoot. After that, both of *P&O* and IncCond stabilize in MPP. But, OCV converge far from MPP.

The Fig. 14 shows that the NN reached immediately the corespondent duty cycle during the variation of temperature or irradiance.

The drawbacks of the NN algorithm are the training of the network before the use and any modification of the system will lead a new training of the neural network.

VI. Conclusion

The non linear characteristic of solar PV system needs an efficient Maximum Power Point Tracking (MPPT) algorithm to control the output power which has a big impact in the efficiency of the solar PV system in order to extract the maximum amount of energy. The proposed algorithm depends on the duty ratio predicted by Neural Network (NN). After the training of the network using 625 samples and the validation of this technique assures high output power in a short time, no overshoot, low oscillation, and more stability comparing with conventional algorithms. The simulation results confirm the satisfactory of the NN algorithm in different environmental conditions by the fast tracking of the Maximum Power Point (MPP). Also, the small Mean Squared Error (MSE) obtained from the NN justify the precision and the stability of the duty cycle.

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