A Novel Global MPPT based on Genetic Algorithms for Photovoltaic Systems under the Influence of Partial Shading

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***Abstract*—This paper presents a novel maximum power point tracking (MPPT) algorithm, based on genetic algorithms (GA). This algorithm is used for searching the global maximum power point (GMPP) for photovoltaic systems affected by partial shading. The "Perturb and Observe" (P&O) algorithm is embedded into the GA function for improving the optimisation process. By adding this functionality to the algorithm, the number of iterations and the population size is low, thus finding the MPP in a short time. Description of this algorithm and its performances will be detailed in this article, verified through simulation and experimental results.**

Keywords—MPPT; Genetic Algorithm; Photovoltaic System; Power Electronics;

I. INTRODUCTION

Photovoltaic (PV) energy became a powerful competitor on the renewable energy market. The control structure and the maximum power point tracking algorithm influence the efficiency and the reliability of the system. A simple MPPT algorithm like Perturb and Observe (P&O) can obtain good results for a system with a single solar panel. For systems where PV panels are stacked in series and in parallel a simple MPPT will lead to huge loses of energy because of the partial shading effect.

The partial shading effect occurs when some solar panels are not uniformly illuminated like the other PV modules from the string. In this situation, the current through the PV panels is ensured by the bypass diodes connected in parallel with each module, which gets shunted when their current is lower than the string current. In order for all panels to be active, the string current has to be smaller than the short circuit current of the PV module with the lowest irradiance.

The bypass diodes from a PV system are the reason of multiple maxima in the power voltage (P-V) characteristic. Many MPPT algorithms have been developed but most of them are based on P&O [1] and Incremental Conductance [2]. These algorithms are easy to implement but fail to find the GMPP under the influence of partial shading.

There is a recent trend in photovoltaic applications that replaces the bypass diodes with power converters, thus eliminating local MPP (LMPP). This concept is named distributed MPPT (DMPPT). Some DMPPT concepts described in the literature are: PV voltage equalization [3-4], series connected DMPPT [5], parallel connected DMPPT [6], differential power processing [7] and microinverters [8-9].

Even though the DMPPT system provides only one MPP from the point of view of the central converter, each panel can have LMPP. By default two or three bypass diodes are included in its internal structure to comply with the IEC 61215 standard. This standard refers to the hot-spot endurance test. GMPPT algorithms are needed to track the global MPP under partial shading conditions for each panel.

The easiest way to search the GMPP is to sweep the entire string voltage [10]. Classical MPPT algorithms have been combined with artificial intelligence methods in order to improve performances and make the tracking less susceptible to surrounding factors. Fuzzy logic is often combined with artificial neuronal networks (ANN) and genetic algorithms (GA) to tune the membership functions, thus obtaining faster convergence time to the MPP and less influence from sudden change of luminosity [11].

In [12] the authors present a fuzzy logic algorithm combined with characteristic scanning in order to find the GMPP. A GA was developed in [13] for a system with only two local MPP. This algorithm is dependent on the parameters of the characteristic. The proposed algorithm is applicable on a system with unknown numbers of LMPP and no previous knowledge of the P-V characteristic.

The article has six main sections. Firstly the partial shading effect is discussed, followed by the next section which describes the GA theory together with the proposed GMPPT. Two important sections, proving the increased performances provided by this algorithm, describe the simulation and experimental results. The final section presents the conclusions.

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II. PARTIAL SHADING PHENOMENON

In a photovoltaic panel the solar cells are stacked together in order to raise the output voltage. In practical experiments there can be mismatching conditions between the solar cells. This happens because of the partial shadowing effect. An important phenomenon that reduces energy harvesting in photovoltaic applications is the partial shadowing effect. The cell with the lowest irradiance determines the current through the whole series string.

When two solar cells with different short circuit current are connected in series, the one with the lowest current will reverse its voltage and absorb power from the other cell. The absorbed power will be dissipated as heat. If the reverse voltage or the junction temperature is not controlled, the hot spot effect will appear.

Different bypass diodes topologies [14] and solar cell configuration [15] have been proposed for improving energy extraction or for protecting the PV module from the hot spot effect. When a solar cell is shaded, Fig. 1a, the bypass diode limits the voltage on this cell. When there is no partial shading, Fig. 1b, the bypass diode has no effect on the circuit. The voltage on the shaded cell is limited to:

$$V_{reverse} = n \cdot V_{oc} + V_{Bdiode} \tag{1}$$

where, $V_{reverse}$ is the reverse voltage drop on the shadowed cell, n is the number of cells which are not shadowed from the group of bypassed cells, V_{OC} is the open circuit voltage of a single solar cell and V_{Bdiode} is the voltage drop of a bypass diode.

Inserting bypass diodes will protect the solar panels but will decrease the extracted energy from the PV modules. Bypass diodes shunt the solar panels that have a lower short circuit current than the string current, thus inserting multiple LMPP. Replacing the bypass diodes with power converters will eliminate the LMPP. This effect can be seen in Fig. 2 where the DMPPT power characteristic has only one MPP and can give more power than the characteristic with bypass diodes.

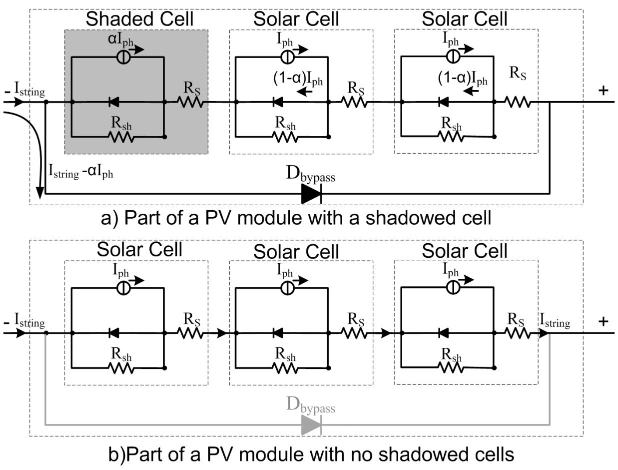

Fig. 1 Solar cell protection with bypass diode.

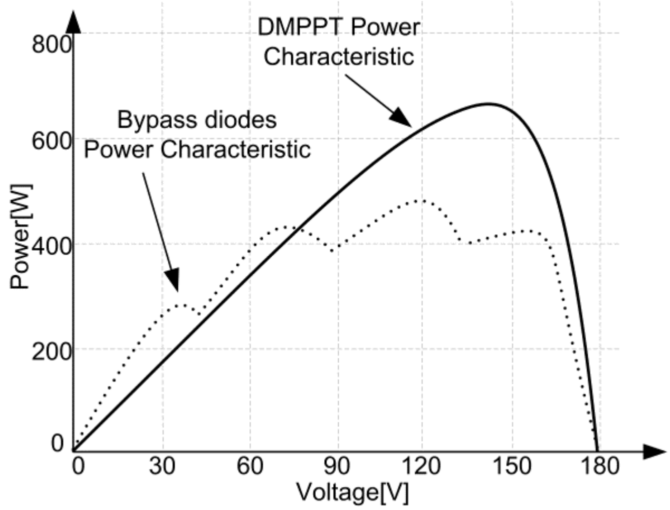

Fig. 2 Difference between a system with DMPPT and a system with bypass diodes.

The DMPPT system eliminates the LMPP from the characteristic of the entire system. The partial shading phenomenon can affect the system and also each solar panel. In Fig. 3 "Panel 3" is not uniformly irradiated. In order to extract the maximum power from this system the DMPPT system must have a GMPPT algorithm on each converter.

The next section presents the proposed genetic algorithm that is applicable on DMPPT systems and also for systems with single inverter, where the input voltage is very high.

III. GENETIC ALGORITHM WITH MPPT

Genetic algorithms are an optimization method based on the principle of natural selection. They represent a random search that finds solutions to an optimization problem. The success of the optimization does not necessarily depend on the initial conditions. The GA convergence has not been yet demonstrated mathematically.

The algorithm optimizes the solutions (membership function, step size) based on the key operators of the GA: selection, crossover, mutation. GA is known to optimize a fuzzy logic controller by tuning their rule base table, membership function or both of them. The optimized fuzzy logic will not be able to find the GMPPT under partial shading.

A selection method that offers good results and it is easy to implement is the "Roulette Wheel". The main idea is that better individuals get higher chance to get selected but it is not guaranteed. To each individual a part of the roulette wheel is assigned depending on their fitness value.

The applied crossover function depends on how the genes are coded. If the genes are coded in binary format, a simple crossover method would be single point crossover. In order to create new offsprings, a random integer number, smaller than the number of genes in a chromosome, sets the position where the parents will be split. If the genes are coded with continuous numbers the children can be obtained from:

$$\begin{aligned} offspring_1 &= \alpha \cdot parent_1 + (1-\alpha) \cdot parent_2 \\ offspring_2 &= (1-\alpha) \cdot parent_1 + \alpha \cdot parent_2 \end{aligned} \tag{2}$$

where α is the crossover rate.

Mutation is used to provide the algorithm new solutions that can not be reached just by applying crossover operations. Each gene is independently altered with a probability called the mutation rate. If the genes are coded in binary format the mutation process will invert the bit value from a random positions. If the genes are coded with continuous numbers, the mutation is done by using:

$$offspring = \pm \beta \cdot offspring + offspring \qquad (3)$$

where β is the mutation rate.

In order to implement GA on a DSP, a function for generating random numbers is needed. In order to obtain true random numbers, a physical signal that is expected to be random has to be measured. Another possibility is to obtain pseudorandom number by using software algorithms that can produce sequences of numbers that appear to be random. This string of numbers depends on an initial value, which determines the randomness of numbers. The equation that was used is:

$$x[n] = (a \cdot x[n-1] + c)\%m \qquad (4)$$

where a=8121,c=28411,m=524287, x[0]=17862 and x[n] is the current random number.

The proposed algorithm incorporates in its structure a classical P&O algorithm in order for the genetic algorithm to converge faster at the final solution.

The structure of the individual for the proposed algorithm is presented in Fig. 4. The population is composed of individual. Each individual has three chromosomes. The first chromosome represents the operating point and the other two chromosomes represent the direction of perturbation and step size of the P&O algorithm. Multiple genes form a chromosome. Each gene is represented by a single bit. For the crossover operation a single point crossover function is used. The mutation probability is 0.1 and crossover probability is 0.8. The population size is 10 and the number of iteration is 15.

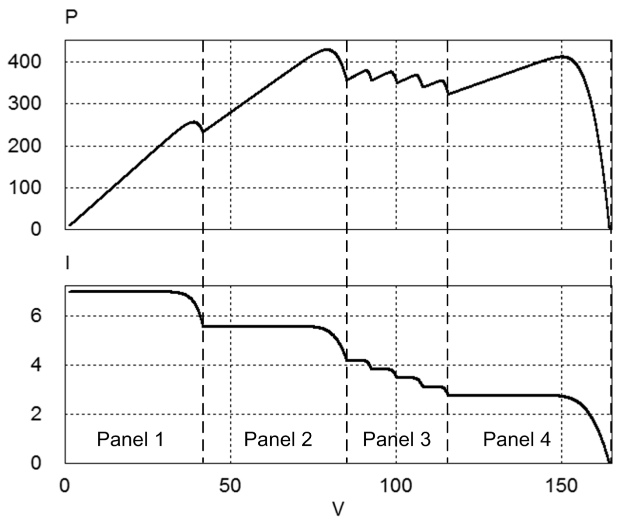

Fig. 3 Partial shading affects each PV panel.

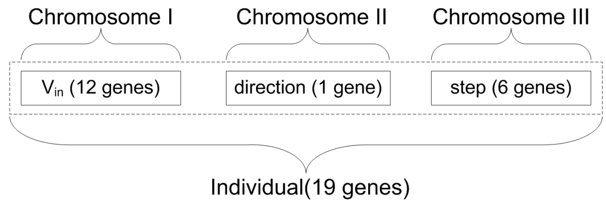

Fig. 4 Structure of the individual.

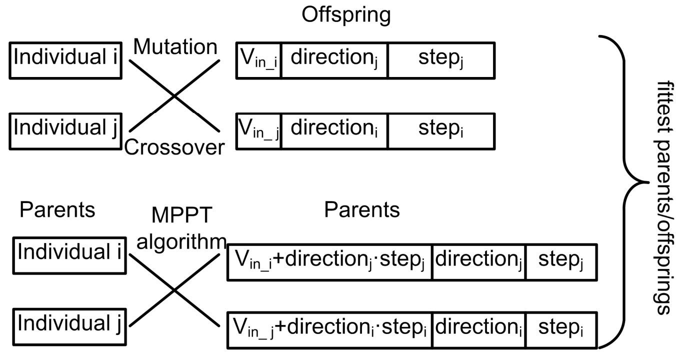

Fig. 5 Innovative part of the GA for maximum power point tracking.

This algorithm has an additional block compared to the usual GA flowchart. Between the mutation and the replacing of the old population with the new individuals, in the GA flowchart, an MPPT algorithm is applied on the parents. A more detailed description of this step can be seen in Fig. 5. The parents exchange the direction and step values between them. The equation that describes the new operating points for the new parents is:

$$\begin{aligned} V_{in\_i} &= V_{in\_i} + direction_j \cdot step_j \\ V_{in\_j} &= V_{in\_j} + direction_i \cdot step_i \end{aligned} \qquad (5)$$

The innovative part of this algorithm is the P&O feature that is embedded into the GA optimisation process by altering the parent's chromosomes. The fittest offsprings and the best parents will replace the old population. With the proposed optimisation, a population size of 10 and a total number of 15 iterations are feasible to implement the GMPPT algorithm.

In the next chapter the algorithm will be tested with a total number of three shading patterns.

IV. SIMULATION RESULTS

In this section the simulation results for the proposed algorithm will be presented. A small scale system was developed in order to test this algorithm. The algorithm can also be applied to systems that have a higher voltage and a higher power.

The panels were modelled with current sources in parallel with diodes. The current sources allow precise and repetitive irradiance level for each panel. A series and parallel resistance was added to each panel to better simulate a real PV module. A bypass diode was mounted on each PV model in order to ensure current flow into the string when partial shading occurs.

The schematic of the system is presented in Fig. 6. A buck converter harvests energy from four solar panels and charges a

12V lead battery. The string can have a maximum of four LMPPT with a V_{OC} of 34V. Because at the output voltage of the converter a 12V lead acid battery is connected, the lowest LMPP (below 8V) can not be tracked and only three local maximum power points will be searched. The short circuit current is varied between 100mA and 500mA. The inductor has a value of 23μH and the input capacitor is 1mF.

In order for the system to have a short tracking time of the GMPP, the converter has to respond very fast to a voltage reference step change, given by the MPPT controller. The GMPPT algorithm needs to change the voltage reference in order to track the optimum operating point. Before changing to a new voltage reference, steady state must be achieved in order to obtain a good reading of the PV panel current and voltage.

The system uses a DSP for implementing three digital control loops: a power loop which is the MPPT algorithm, a voltage loop on the solar panel voltage and an inner current loop for short circuit protection. The advantage of having two control loops (voltage and current) for stabilizing the system eases the compensation process and gives a better step response on reference changes.

The shading patterns that are used for testing the proposed algorithm are illustrated in Fig. 7. Each characteristic of the solar panel was chosen in order to show how the algorithm behaves in a certain condition. The pattern from Fig. 7a presents a situation where there are four LMPP from which three of them have almost the same power level. The next characteristic from Fig. 7b presents two GMPP that are close to one another. The last pattern, Fig. 7c presents two GMPP that are far to one another.

The simulations for the first shading pattern are presented in Fig. 8. It can be seen that the genetic algorithm presents repeatability in finding the GMPP even though random numbers are used in the algorithm to converge to the final solution. By combining P&O with GA, it can be seen on the voltage waveform that the tracking is similar to a perturb and observe algorithm applied on systems with a single maxima. The difference is that the proposed algorithm searches the GMPP on systems with partial shading.

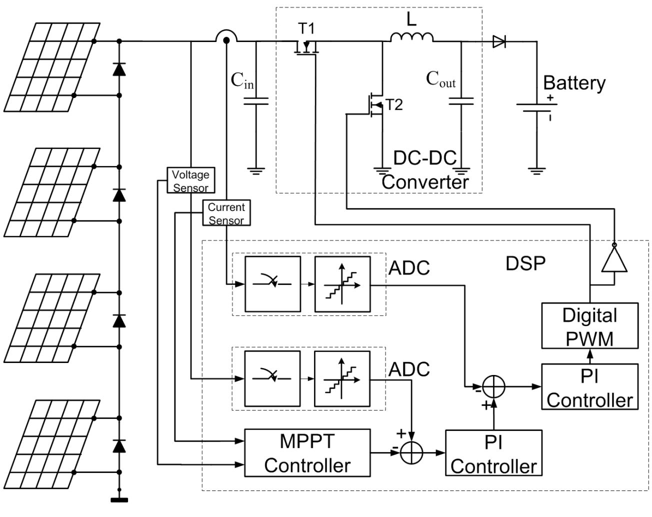

Fig. 6 Schematic of the tested system.

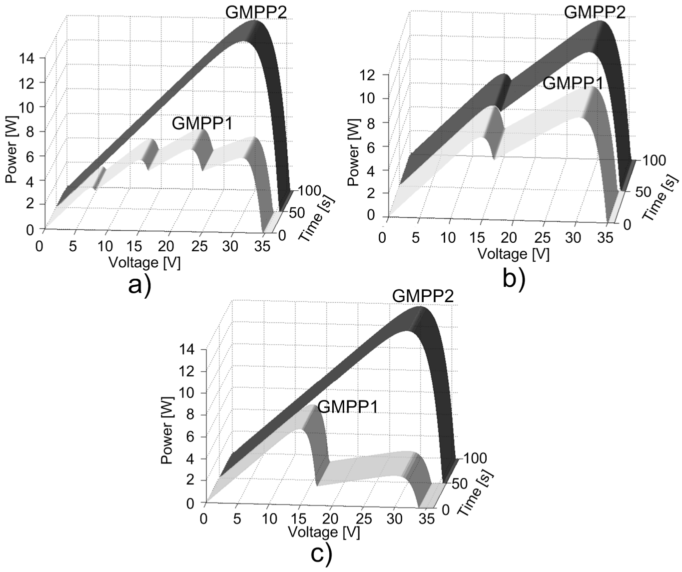

Fig. 7 Shading patterns for testing the GMPPT algorithms.

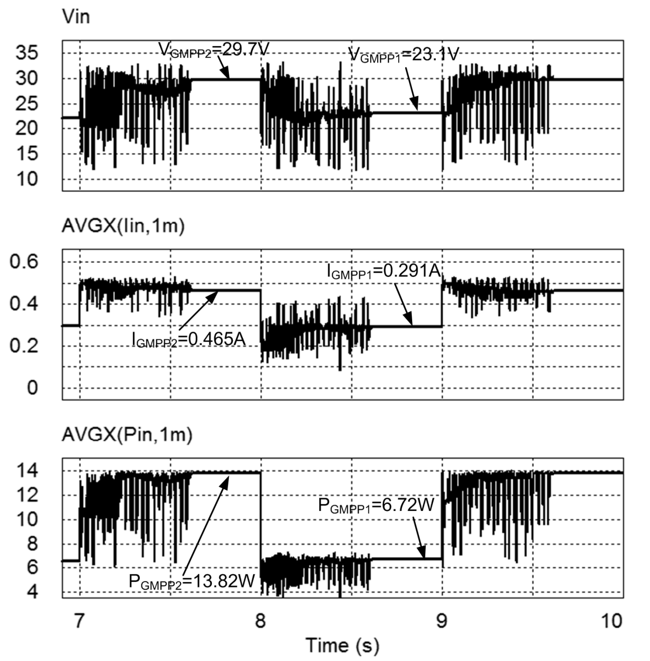

Fig. 8 Simulation results for the genetic algorithm applied on the first shading pattern.

In Fig. 9 there is a zoom in on the voltage and current waveforms. It can be seen that there are two types of perturbations. The small perturbation steps are caused by the P&O applied to the parent from the population. This is represented by the values in the enclosed grey area on the voltage waveform. The big perturbation steps are caused by the mutation that happens to an individual of the population. This is represented by values that are placed outside of the grey area.

The simulations for the second pattern are presented in Fig. 10. For this pattern the GMPP of the first characteristic is close to the GMPP of the second characteristic. It can be seen that the GA can distinguish between the two values. The small difference between the two GMPP is tracked with the P&O embedded into the GA optimisation process.

The simulation for the third pattern that was presented in Fig. 7c is presented in Fig. 11. This pattern shows that the two GMPP of the two characteristics are far from one another. The reason that the algorithm succeeds in finding the GMPP every time with repetability of the optimum operating values is due to the mutation operation. The mutation brings the operating point close to the GMPP and then the P&O searches it more acurately.

A simulation was made to compare the results of the proposed algorithm with a standard string voltage sweep method. The GA has better results. The GA also sweeps the entire string voltage, but in a random way and after it finds the zone with the highest power it searches with good accuracy the optimum operating point.

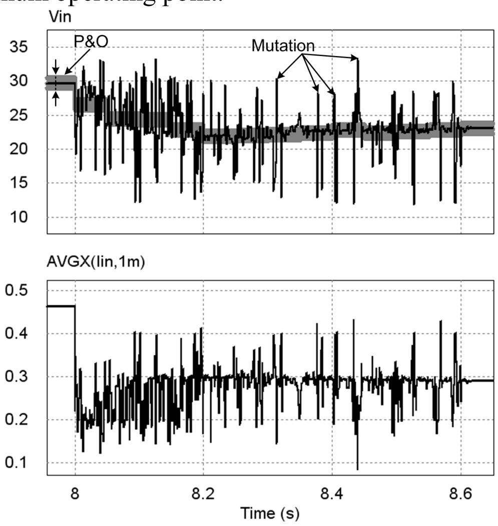

Fig. 9 Zoom in on GMPPT algorithm convergence.

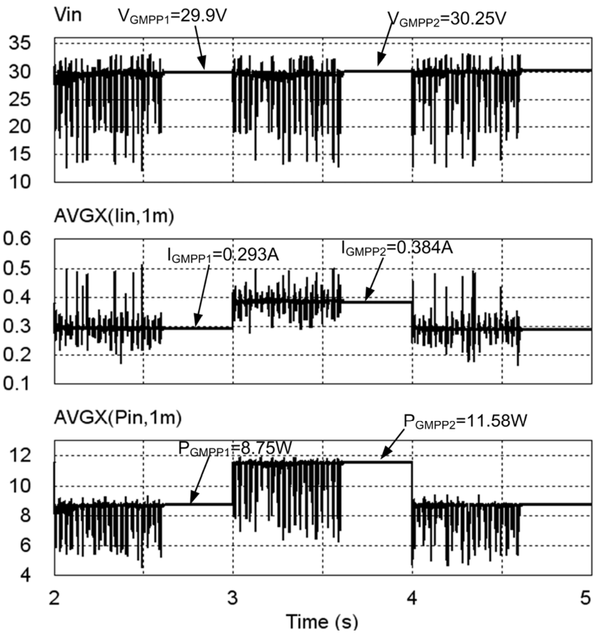

Fig. 10 Simulation results for the genetic algorithm applied on the second shading pattern.

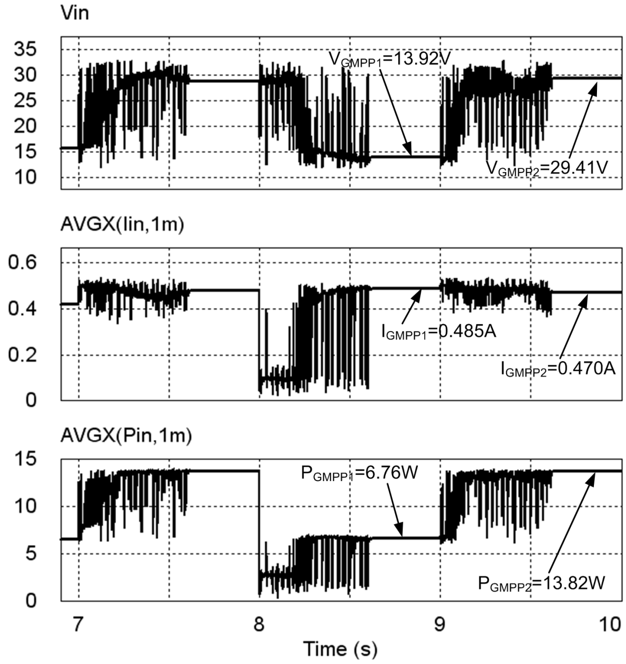

Fig. 11 Simulation results for the genetic algorithm applied on the third shading pattern.

V. EXPERIMENTAL RESULTS

Experimental results will be presented next for the proposed GMPPT algorithm. The algorithm and the control loops are implemented on a TMS320F2808 DSP from Texas Instruments. The patterns from Fig. 7 are implemented with current sources in parallel with strings of diodes. In this way repetitive and exact irradiance level can be reproduced in the laboratory.

The experimental results for all patterns are presented in Fig. 12, Fig. 13 and Fig. 14. It can be seen that the experimental results are very similar to the simulation results from Fig. 8, Fig. 10 and Fig. 11.

The current loop is sampled at 50KHz and the voltage loop at 25KHz. The control functions are computed in the interrupt of the analog to digital converter.

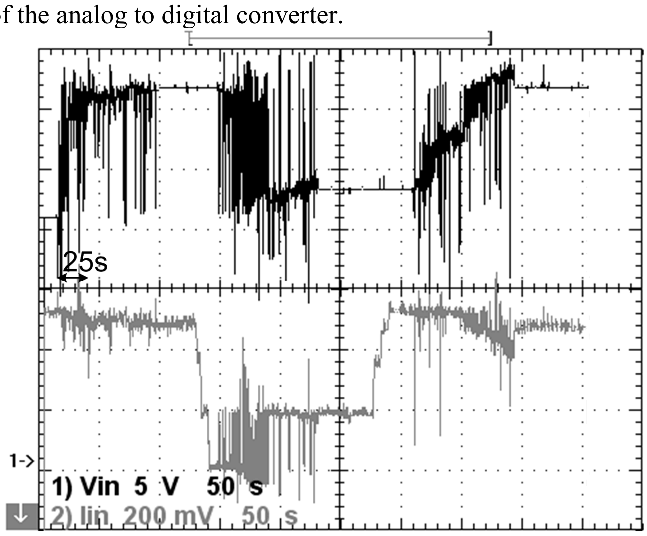

Fig. 12 Experimental results for proposed GA for the first shading pattern.

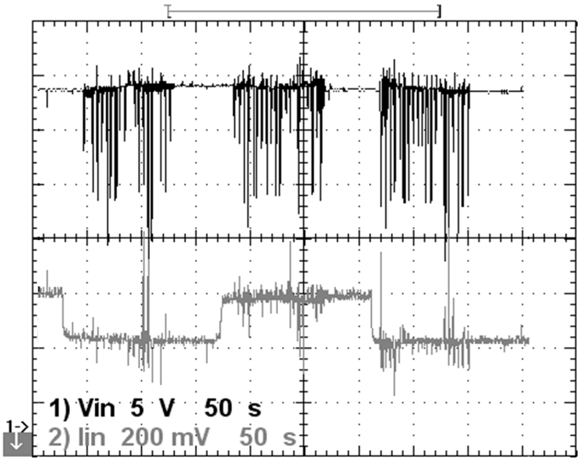

Fig. 13 Experimental results for proposed GA for the second shading pattern.

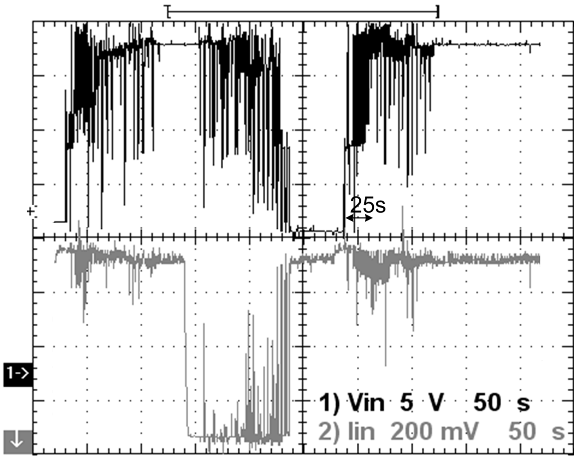

Fig. 14 Experimental results for proposed GA for the third shading pattern.

The GA algorithm is computed outside the interrupts and it does not interfere with the computation of the control loops. The GA algorithm is computed in 1ms. The change between two successive operating points (individuals) is of 300ms.

There are situations where the GMPP is found before all iterations are implemented but with small variation around the optimum operating point. The time for tracking the GMPP can vary from a maximum of 75s (when all iterations have been validated) to as low as 25s (Fig. 12 and Fig. 14). In Fig. 13 the GMPP is found immediately but it needs the P&O function to bring the operating point as close as possible to new GMPP.

VI. CONCLUSIONS

In this paper a novel global maximum power point tracking algorithm was presented for PV systems affected by partial shading. A P&O algorithm was embedded into the GA optimization function. The effects of adding the P&O into the genetic algorithm were analysed and it can be concluded that the more functionalities are added into the GA optimization problem, the faster the final solution will be obtained. In this way the population size and the number of iterations is small. The theoretical background is validated through simulation and experimental results.

For future research, the influence of the number of genes in the chromosome (V_{in}, step) will be studied. For better randomized numbers, a function will be implemented based on chaos theory.

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