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A new variable step size neural networks MPPT controller: Review, simulation and hardware implementation

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ABSTRACT

In this paper, two new Artificial Neural Network MPPT controllers based on fixed and variable step size have been proposed and investigated. The data required to generate the ANN model are generated using the classical Perturbation and Observation algorithm. The neural network MPPT controller is developed in two steps: the offline step required for training of different neural networks parameters in order to find the optimal neural network MPPT controller (structure, activation function and training algorithm) and the Online step where the optimal neural network MPPT controller is used in PV system. The performance of the proposed variable step size and fixed step size ANN-MPPT methods are analyzed under different operating conditions using Matlab/Simulink. To validate the simulated system hardware implementation of the proposed algorithms was carried out using experimental prototype MPPT based on Flyback converter connected to Solarex MSX-60 (4 panels) and dsPIC30F4011 control circuit. Analysis and comparative study between the proposed fixed and variable step size ANN-MPPT controllers have been presented, showing a real contributions in term of tracking accuracy, response time, overshoot and steady state ripple. In addition, this paper can be considered as a review study on ANN-MPPT methods for PV systems.

1. Introduction

Today, demand for electricity is growing and becomes increasingly important for humanity, and it's an important factor for economic development. To these reasons, many countries have turned to new forms of green energy called "renewable energy" that are currently too expensive and relatively inefficient. Renewable energy is the energy which comes from natural resources such as sunlight, wind, rain, tides and geothermal heat. These resources are renewable and can be naturally replenished. There are many remote sites in the world powered by independent power generation systems. These generators use local renewable sources. There are photovoltaic panels, wind turbines, biomass, geothermal, etc. Electricity from renewable sources is intermittent and dependent on characteristic of the site as well as climatic conditions. These renewable generators are typically coupled to a storage system ensuring continuous availability of energy [1,2].

Among those energy sources, solar energy, free and abundant in most parts of the world, has proven to be an economical source of energy in many applications. Photovoltaic (PV) has been continuously growing at a rapid pace over the recent years, used in many applications such as water supply in rural areas, battery charging, mountain cabins, light sources, water pumping, meteorological measurement systems, highway/traffic conditions, island electrification and satellite power systems [2,3]. The performance of photovoltaic systems depends mainly on the irradiance, temperature, weather conditions, thermal characteristics, module material composition and mounting structure. Many advances and researches regarding the development of PV technology have been adopted and funded in several countries such as efficiency, solar materials, DC/DC converters, MPPT methods, grid-connected photovoltaic system, etc.

Although the aforementioned advantages of PV systems, it still presents some drawbacks comparing to conventional energy resources especially its high fabrication cost, low energy conversion efficiency, and nonlinear characteristics. The overall system cost can be reduced using high efficiency power trackers which are designed to extract the maximum possible power from the PV module (maximum power point tracking, MPPT) [4–6]. A variety of MPPT methods have been developed and improved continuously. These methods include perturb and observe (P & O) [7–9], Incremental Conductance (IC) [10–12], Hill Climbing (HC) [13–15], fractional open-circuit voltage [16,17], fractional short-circuit current [18,19], neural network [20], fuzzy logic methods [21], and genetic algorithms [22]. These techniques differ in

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many aspects such as required sensors, complexity, cost, range of effectiveness, oscillation around the MPP, convergence speed, correct tracking when irradiation and/or temperature change and hardware implementation.

Recently, artificial neural network technique has provided new interest in PV systems. Neural networks can be trained off-line for nonlinear mapping and can then be used in an efficient way in the on-line environment [23]. The main advantage of neural network is that it do not require an accurate mathematical model and they can detect complex nonlinear relationships between dependent and independent variables. Due to previous disadvantages, many MPPT controller using artificial neural network (ANN) have been developed [24–28].

Despite, a several maximum power point tracking algorithms based on fixed step have been developed and improved, some problems are unavoidable such as the oscillation around the MPP and accuracy and failure accuracy especially accentuated under shading conditions. To overcome these drawbacks, modified MPPT with variable step size is proposed [11,29,30].

In this work, the ANN approach is proposed to provide the power converter duty cycle under different atmospheric conditions. Since trained, neural network can quickly map nonlinear relationship between input data and the output. The data required to generate the ANN model are obtained using the principle of perturbation and observation (P & O) method. The neural network MPPT controller is developed in two steps: the offline step required for the training of different set of neural network parameters in order to find the optimal neural network controller (structure, activation function and training algorithm) and the On-line step where the optimal neural network MPPT controller is used in PV system. The P & O algorithm used for the generation of training data as well as proposed neural network MPPT controllers are simulated and tested using Matlab/Simulink model under different atmospheric conditions. To verify the efficiency of proposed ANN-MPPT controllers, hardware implementation was carried out using Flyback converter connected to Solarex MSX-60 (04 panels) and dsPIC30F4011 control circuit. Both, simulation and experimental design are provided in several aspects, in which comparative study between the proposed fixed and variable step size ANN-MPPT controllers have been presented and discussed in details.

2. Related works on the use of neural networks in PV MPPT

Recently, artificial intelligence techniques are becoming the most leading approaches used in PV systems and becoming more and more popular, since is regarded as capable of resolving a significant problems of conventional method such as oscillation around the MPP, the convergence speed, failure accuracy under fast changing atmospheric conditions, etc.

Artificial intelligence MPPT techniques includes artificial neural networks [31], fuzzy logic [32], and genetic algorithm techniques [33], particle swarm optimization [34], sliding mode [35], etc. These techniques can be used to perform nonlinear statistical modeling and provide a new alternative to logistic regression. In addition, many combined artificial intelligence MPPT methods have been developed such as genetic algorithm-fuzzy logic controller [36], genetic algorithm-neural networks [37] and optimization of a fuzzy logic controller using particle swarm optimization [38].

Among previous artificial intelligence techniques, neural networks have become increasingly popular since they require less formal statistical training, simplicity and ease of implementation, they can detect complex nonlinear relationships between dependent and independent variables, they don't require an accurate mathematical model, in addition, several ANN training algorithms are available and can offer a large number of solutions.

From the use of NN concept have resulting a wide research field and applications in PV systems: PV Irradiation forecasting [39], PV model parameters identification [40], PV system sizing [41], PV structure optimization [42] and PV MPPT strategies [43–45]. This last application had focused the attention of many researchers and engineers due to its impact on whole system performances. The MPPT, considered as the heart of PV system, adjusts the output power of inverter or DC converter in order to supply reliable energy to the load. The rest of this section constitutes a brief review of the use of ANNs in PV system MPPT techniques.

In Ref. [46,56,57], authors have conducted several studies on the use of brushless motor drive for heating, ventilating and air conditioning. In the first study, the brushless motor drive is used as a load for a photovoltaic system. The MPPT controller is based on a genetic assisted, multi-layer perceptron neural network (GA-MLP-NN) structure and includes a DC–DC boost converter. Genetic assistance in the neural network is used to optimize the size of the hidden layer. The proposed MPPT controller implemented on DSP, provides an average power increase of 25.35%. In the second study, an ANN was used to determine the reference voltage in real time, dependent upon irradiance and temperature. The dataset used to train the ANN was obtained using experimental measurements, and a relation between the inputs (insolation and temperature) and output (V_{MPP}) was established. Due to large dataset used to train the ANN, the GA was used to keep the most decisive data and remove insignificant data. In the third one, the application of GA into ANN is regarded as the process of searching for optimal topology for ANN.

In Ref. [47,55], authors propose a maximum power point tracking technique based on Extension Neural Network (ENN). The proposed ENN MPPT algorithm can automatically adjust the step size to track the PV array maximum power point. The presented method is able to effectively improve the dynamic response and steady state performance of the PV systems simultaneously compared with the conventional fixed step size perturbation and observation and incremental conductance methods. The simulation results realizing using PSIM circuit-based model demonstrate the effectiveness of the proposed MPPT method. On the other hand, the proposed ENN MPPT algorithm needs less constructed data and simple learning procedure making it easily implemented using microcontroller platform.

In Ref. [48], authors propose a novel voltage-based maximum power point tracking technique. The optimal voltage factor is instantaneously determined by a neural network instead constant parameter assumed in other voltage-based MPPT methods. The simulation results of the proposed MPPT algorithm applied to a Buck converter to regulate the output power at its maximum possible value show greater output power up to 3.5% compared to the PV system without the MPPT strategy. On the other hand, The proposed neural network based method eliminates the deficiency of the "Look-Up Table" method that needs a lot of storage memory to save all the environmental conditions.

In Ref. [49], authors propose a novel MPPT that uses an online learning neural network and the perturbation and observation method to solve its low performances in case fast changing solar radiation. The proposed MPPT is able to learn the photovoltaic properties while operating the P & O under gradually changing solar radiation conditions, and accomplishes the quick tracking of the MPP in case of fast changing solar radiation. The simulation results show very efficiently even when the solar radiation changes rapidly.

In Ref. [50], authors propose a novel MPPT system for partially shaded PV array using artificial neural network and fuzzy logic with polar information controller. In this study, the ANN with three layer feed-forward is trained once for several partially shaded conditions to determine the global MPP voltage; while the fuzzy logic with polar information controller uses the global MPP voltage as a reference voltage to generate the required control signal for the power converter. The proposed system has been verified through the experimental real-time simulator using dSPAPE platform for different size of PV array with series–parallel, bridge linked, total cross tied configurations. The results show that more power can be extracted and overall energy yield can be increased with the proposed system under from lightly to heavily partially shaded conditions.

In Ref. [51], authors propose an intelligent control strategy for the MPPT of a PV energy system based on four-layer fuzzy neural network controller (FNNC), which combines the reasoning capability of fuzzy logical systems and the learning capability of neural networks, to track the MPP. The parameters in the FNNC are updated adaptively by observing the tracking error using the derived learning algorithm. The RBFNN is designed to provide the FNNC with the gradient information. The experimental results show that the FNNC tracks the MPP quickly and steadily, exhibits good robustness to the parameter variants and external load disturbances, and performs much better compared with the traditional FLC.

In Ref. [52], authors present a novel methodology for maximum power point tracking of a grid-connected 20 kW photovoltaic system based on neuro-fuzzy estimator. The developed neuro-fuzzy network consists of two stages; the first one is a fuzzy rule-based classifier, the second one is composed of three multi-layered feed forwarded ANNs trained offline using experimental data from a real PV system installed at the engineering campus of Tokyo University of Agriculture and Technology. Maximum power operation was achieved by tracking the reference voltage estimated by the neuro-fuzzy network through a DC–DC converter. Simulation results under several rapid irradiance variations proved that the proposed MPPT method fulfilled the highest efficiency comparing to a conventional single neural network and the perturb and observe algorithm showing also a good to faithfully emulate the dynamic and nonlinear behavior of a photovoltaic generator under a large wide of climatic conditions.

In Ref. [53], authors present a new MPPT method based on artificial neural network. The new combined method is established on the three-point comparing method and ANN-based PV model method. The ANN is used to guide the reference operation point that close to the MPP quickly; then the three-point comparing is used to track the exact MPP. The simulations results obtained under Matlab environment show that the proposed ANN-MPPT decreases the tracking time of the three-point comparing as well as proving the effectiveness of the proposed algorithm.

In Ref. [54], authors propose a stand-alone solar and diesel–wind hybrid generation system using an intelligent power controller to effectively extract the maximum power from the wind and solar energy sources. The intelligent controller consists of a radial basis function network (RBFN) used for the solar system and an improved ELman Neural Network (ELNN) is used to control the pitch angle of wind turbine. The diesel generator is used to regulate the load frequency by imposing the rotor currents with the slip frequency. The Matlab/Simulink simulations results show more efficiency, a better transient and more stability, even under disturbance.

In Ref. [58], the author presents the optimum photovoltaic water pumping system using maximum power point tracking technique. In this study, an adaptive controller with emphasis on Nonlinear Autoregressive Moving Average (NARMA) based on artificial neural networks approach is applied in order to optimize the duty ratio for PV maximum power at any irradiation level. The model-based design of neural network controller is realized using an indirect data-based technique where a model of the plant is identified on the basis of input–output data. The proposed controller has the advantages of fast response and good performance. The considered system with the proposed controller has been tested through a step change in irradiation level. Simulation results of the proposed artificial neural network (ANN) controller compared with a PID controller demonstrate the effectiveness and superiority of the proposed approach. The results also show that the MPPT techniques add about 38% more performance, with zero steady state error and with settling time less than one second.

In Ref. [59], authors propose a novel MPPT algorithm using neural network compensator based on the slope of power versus voltage. The uncertainties of solar irradiation conditions, ambient temperature, and the load electrical characteristics in PV systems are compensated by a neural network. While the PI controller is used to determine the duty cycle of dc/dc converter. The simulation and experimental results prove the validity of the proposed MPPT controller under a certain solar irradiation and a partially shaded condition, respectively.

In Ref. [60], authors propose an efficiency MPPT based on artificial neural network suitable for solving non linear relation. The proposed ANN-MPPT is compared to the conventional perturbation & observation algorithm. The comparison results show that ANN-MPPT outperforms the traditional P&O MPPT in term of efficiency and the reduction of the output oscillations around the MPP.

In Ref. [61], authors propose a technique to adjust the changing step size of Flyback converter to achieve both acceptable tracking time and low power oscillation. The proposed technique uses an artificial neural network to estimate the appropriate modulation step size. In this ANN, the irradiance is adopted as the input. Simulation results confirm that the proposed neural network based inverter can find the appropriate changing step size adequate for any irradiance conditions.

In Ref. [62], authors present a neural network based incremental conductance IC algorithm for maximum power point tracking in PV system. The ANN is used to supply the voltage V_{ref} to the modified IC method. The ANN is trained in off-line using experimental data under various atmospheric conditions. The trained ANN is used for online estimation of reference voltage for the feed-forward loop. The PV system along with the proposed MPPT algorithm was simulated using Matlab/Simulink Simscape toolbox. The simulated system was evaluated under uniform and non-uniform irradiation conditions and compared to perturb and observe and fuzzy based modified hill climbing algorithms showing that the proposed approach is effective in tracking the MPP under partial shading conditions with less response time than other two methods. The simulation results have been validated by hardware implementation using FPGA.

In Ref. [63], authors suggest a photovoltaic/thermal (PV/T) control algorithm based on artificial neural network to detect the optimal power operating point by considering PV/T model behavior. The optimal power operating point computes the optimum mass flow rate of PV/T for a considered irradiation and ambient temperature. The simulations results of the proposed control demonstrate great concordance between optimal power operating point model based calculation and ANN outputs.

In Ref. [64], the author proposes a novel method to determine the characteristics of silicon solar cell, module and plastic solar cell. In this method, a feed-forward artificial neural network with Lambert W function are used to determine the I-V and P-V characteristics. Five model parameters of the solar cell and module are calculated using the proposed technique which compares the Lambert W function representation of the I–V characteristic with the learned feed-forward neural network model of the I–V relation. Simulation results show a very good agreement between the calculated characteristic curves and experimental data as well as its superiority compared with other related methods in term of current and power errors even at the Maximum Power Point.

In Ref. [65], authors propose two fast and accurate digital MPPT methods for fast changing environments using piecewise line segments or cubic equation to approximate the maximum power point locus. In this study, a neural network-based program which can be used to calculate the parameters of the estimated MPP locus is also developed and embedded into the proposed digital MPPT system. Simulation and experimental tests are conducted to validate the effectiveness and correctness of the proposed methods. The results prove the advantages of the proposed system in term of low computation requirement, fast tracking speed and high static/dynamic tracking efficiencies.

In Ref. [66], authors analyze the performance of ANN, P&O–ANFIS and PSO–ANFIS MPPT algorithms by stand-alone PV system. The configuration for the proposed system is designed and simulated using Matlab/Simulink and implemented in 16F877A microcontroller. In this study, a combination of an interleaved soft switched boost

Table 1
Summary of neural networks based maximum power point tracking techniques.

	Reference	Year	Tech.	Remarks
Neural Network Direct Method	Akkaya et al.[46]	2007	ANN	The MPPT controller is based on a genetic optimization of the size of the hidden layer multi-layer perceptron neural network structure. The proposed MPPT controller implemented on DSP, provides an average power increase of 25.35%
	Chao et al.[47]	2009	ANN	The MPPT technique is based on extension neural network (ENN) adjusting automatically the step size to track the MPP. The simulation results realizing using PSIM demonstrate the effectiveness of the proposed MPPT method.
	Habibi and Yazdizadeh[48]	2009	ANN	The voltage-based MPPT using optimal voltage factor instantaneously determined by a neural network. The simulation results show greater output power up to 3.5%
	Kohata et al.[49]	2009	ANN	The MPPT uses and learning neural network and the P & O method to solve the low performances of conventional P & O efficiency. The simulation results show very efficiently even when the solar radiation changes rapidly.
	Zhang and Cheng[53]	2011	ANN	The MPPT method is established on the three-point comparing method and ANN-based PV model. The ANN is used to guide the reference operation point close to the MPP quickly; while the three-point comparing is used to track the exact MPP. The simulations results prove the effectiveness to decrease of tracking time of the three-point comparing method.
	Lin et al.[54]	2011	ANN	The MPPT consists of a radial basis function network used for the solar system and an improved Elman neural network used to control the pitch angle of wind turbine. The simulations results show more efficiency, a better transient and more stability, even under disturbance.
	Chao et al.[55]	2011	ANN	The incremental conductance MPPT is based on extension theory and neural network able to adjust the MPP automatically. The results demonstrate the efficiency improvement using the proposed method.
	Kassem[58]	2012	ANN	The MPPT uses an adaptive controller with emphasis on nonlinear autoregressive moving average based on artificial neural networks approach to optimize the duty ratio for PV converter. The results show performance improvement up to 38% with zero steady state error and with settling time less than one second.
	Yong et al.[60]	2012	ANN	The proposed MPPT based on neural network is compared to the conventional P & O algorithm. The comparison results show that ANN-MPPT outperforms the traditional P & O MPPT in all performances measure.
	Konghuayrob and Kaitwanidvilai[61]	2012	ANN	The MPPT uses neural network to adjust the step size of Flyback converter to achieve both acceptable tracking time and low power oscillation. Simulation results confirm that the proposed controller can find the appropriate changing step size adequate for any irradiance conditions.
	Ben Ammar et al.[63]	2013	ANN	The ANN is used to control the optimal power operating point of the PV/Thermal system. The controller computes the optimum mass flow rate of PV/T for a considered irradiation and ambient temperature. The simulations results demonstrate great concordance between the model based calculation and ANN outputs.
	Liu et al.[65]	2013	ANN	Two MPPT methods based on piecewise line segments or cubic equation to approximate the maximum power point locus. The neural network is used to calculate the parameters of the estimated MPP locus. The results prove the low computation requirement, fast tracking speed and high static/dynamic tracking efficiencies.
	Velilla et al.[67]	2014	ANN	The ANN models are trained using monitoring system of two different solar modules technologies records. The errors between the experimental data recorded and the results of the ANN are about 1.6 W and 0.29 W for each model with a 50% confidence in the results.
	Dubey[69]	2014	ANN	The ANN-MPPT is based on hysteresis current controlled converter developed with three level techniques with fixed band and load variation value determined with output current THD lower than 5%. The simulation results demonstrate very satisfactory efficiency (99%).
	Askarzadeh[71]	2014	ANN	The ANN is used to predict the voltage of a PV module as a function of current, temperature and solar irradiance. The model accuracy is investigated by varying the number of hidden layers and training algorithms. Simulation results show that the back propagation network with one hidden layer with normalized data and trained by Levenberg–Marquardt algorithm outperforms the other the other studied networks.
	Khaldi et al.[73]	2014	ANN	The MPPT is based on neural network and compared to P & O and IC algorithms. The simulation results carried-out show the efficiency improvement and the oscillations reduction using the proposed ANN-MPPT compared to the P & O and IC algorithms
	Dounis et al.[74]	2015	ANN	The MPPT uses a direct adaptive neural control method operating on MPP and improves the performance of solar energy conversion efficiency. The MPP is reached very rapidly, the time response in the transient states is extremely short and the fluctuations in the steady state are considerably reduced.
	Messalti et al.[76]	2015	ANN	The MPPT uses neural network model trained in offline mode using the P & O algorithm and used in online mode to track the MPP under different atmospheric conditions. The results prove the efficiency of NN compared to conventional P & O.
Neural Network Combined Methods	Syafaruddin et al.[50]	2009	ANN-FZ	The MPPT uses the neural network to track the global MPP. While the fuzzy controller uses the global MPP voltage as a reference voltage for power converter. Simulation and experimental results show that more power can be extracted and overall energy yield can be increased.
	Li et al.[51]	2009	ANN-FZ	The MPPT based on four-layer fuzzy neural network controller. The neural network is designed to provide the FLC with the gradient information. The experimental results tracks the MPP quickly and steadily and exhibits good robustness to the parameter variants and external load disturbances.
	Chaouachi et al.[52]	2010	ANN-FZ	The MPPT uses a fuzzy rule-based classifier and three multi-layered feed forwarded ANNs trained offline using experimental data from

(continued on next page)

Table 1 *(continued)*

Reference	Year	Tech.	Remarks
			a real PV system. Simulation results prove the efficiency of the proposed MPPT compared to a conventional single neural network and P & O algorithms.
Kulaksiz et Akkaya[56]	2012	ANN-GA	An ANN trained using experimental measurements was used to determine the reference voltage in real time, dependent upon irradiance and temperature. The GA was used to remove insignificant data.
Kulaksiz et Akkaya[57]	2012	ANN-GA	The application of GA into ANN is regarded as the process of searching for optimal topology for ANN used as MPPT controller for the brushless motor drive is used as a load for a photovoltaic system.
Tsai et al.[59]	2012	ANN-PI	The MPPT uses neural network to compensate The uncertainties of solar irradiation conditions, ambient temperature, and the load electrical characteristics in PV systems; while the PI controller is used to determine the duty cycle of dc/dc converter. The simulation and experimental results prove the validity of the proposed MPPT.
Punitha et al.[62]	2013	ANN-FZ	The MPPT uses neural network trained in off-line using experimental data to supply the voltage V_{ref} to the modified IC method. The proposed approach is rapid compared conventional P & O and Fuzzy based Modified Hill Climbing algorithms. The simulation results have been validated by hardware implementation using FPGA.
Fathabadi[64]	2013	ANN-LW	A feed-forward artificial neural network combined with Lambert W function is used to determine the I-V and P-V characteristics of silicon solar cell module and plastic solar cell and compared to the five model parameters. The simulation results show a very good agreement between the calculated characteristic curves and experimental data.
Muthuramalingam and Manoharan[66]	2014	ANN-PSO	The ANN, P & O–ANFIS and PSO–ANFIS MPPT algorithms have been analysis. An adaptive neuro-fuzzy inference system trained by data derived from a particle swarm optimization is used to drive an interleaved soft switched boost converter running by a set of two photovoltaic panel with a distributed MPPT. Results prove the effectiveness of the PSO–ANFIS.
Chekired et al.[68]	2014	ANN-FZ-GA	A comparison between neural networks, fuzzy logic, genetic algorithm and hybrid systems MPPT and their possible implementation into FPGA. The best controller is tested in real-time co-simulation using FPGA Virtex 5. The results confirm the good tracking efficiency and rapid response of the different methods under variable temperature and solar irradiance.
Gupta et al.[70]	2014	ANN-FZ	The MPPT using artificial neural network and fuzzy logic control are considered. The results show that both the techniques were able to track the MPP effectively. The ANN based MPPT has a better response with negligible oscillations than FLC.
Bendib et al.[72]	2014	ANN-FZ	The MPPT uses an artificial neural networks to estimate the MPP voltage used as a reference by the fuzzy logic controller to generate the PWM signal of DC-DC converter. The results prove the performances improvement in terms of MPP precision and tracking speed.
Rezvani et al.[75]	2015	ANN-GA-FZ	The PV MPPT is realized using artificial neural network trained by data that are optimized by GA. The control of turbine output power in high wind speeds is realized using pitch angle control technique by fuzzy logic. The results show that the ANN-MPPT tracks the MPP effectively and meet the load demand with less fluctuation around the MPP.

converter (ISSBC) run by a set of two photovoltaic panel with a distributed MPPT managed by an adaptive neuro-fuzzy inference system trained by the training data derived from a particle swarm optimization. The ISSBC is followed by a single phase cascaded H bridge five-level inverter driven by the individual DC outputs of the ISSBC, with selective harmonic elimination scheme to eliminate typically the seventh order harmonics. The use of the ISSBC guarantees mitigation of ripple and it is meant to handle higher currents with minimal switching losses. Simulation and experimental results prove that the PSO–ANFIS model of distributed MPPT scheme of control outperforms other schemes of control for MPPT.

In Ref. [67], authors analyses a monitoring system of two different solar modules technologies, a mono-crystalline 55 W silicon and a flexible organic solar module of 12.4 W, were the temperature, relative humidity, and irradiance were monitored during the observation period under outdoor exposure. These records have been used to train, validate and testing of an artificial neural network model where the electrical power of the modules is considered as output. The reliability of the ANN models were evaluated through the standard deviation and dispersion of the errors between the experimental data recorded and the results of the ANN, obtaining an error of about 1.6 W and 0.29 W for each model with a 50% confidence in the results. These ANN models were subjected to a sensitivity analysis with respect to the input variables. From these analyses was observed a remarkable performance of the organic module at lower irradiance values, highlighting the increased power generated for relative humidity below 80%. On the other hand the organic module showed important performances for irradiance less than 400 W/m^2 where the silicon module failed to show adequate performance effectively. This tool allows prediction of the performance of the two photovoltaic technologies evaluated here at different environmental conditions.

In Ref. [68], authors present a comparison between four intelligent methods used in tracking the maximum power point and their possible implementation into a reconfigurable field programmable gate array (FPGA) platform. The investigated methods are neural networks, fuzzy logic, genetic algorithm and hybrid systems (e.g. neuro-fuzzy or ANFIS and fuzzy logic optimized by genetic algorithm). In this study, a complete simulation of the photovoltaic system with intelligent MPP tracking controllers using MATLAB/Simulink and ModelSim environment is given as well as the different steps to design and implement the controllers into the FPGA. The best controller is tested in real-time co-simulation using FPGA Virtex 5. The comparative study has been carried out to show the effectiveness of the developed methods in terms of accuracy, rapidity, flexibility, power consumption and simplicity of implementation. The results confirm the good tracking efficiency and rapid response of the different methods under variable temperature and solar irradiance conditions.

In Ref. [69], author proposes an ANN-MPPT based on hysteresis current controlled converter developed with three level techniques with fixed band and load variation value determined with output current THD lower than 5%. In this system, an ANN is used as maximum power tracking controller. System performance is measured in terms of the efficiency of the MPPT controller with very satisfactory (efficiency of 99%).

In Ref. [70], authors investigate two intelligent techniques (artificial neural network and fuzzy logic control) used in MPPT controllers. Both MPPT techniques are implemented and their performance analyzed Matlab/Simulink environment. The results show that both the techniques were able to track the maximum power point effectively, but ANN based MPPT has a better response with negligible oscillations than FLC.

In Ref. [71], authors investigates the voltage prediction of a PV module as a function of current, temperature, and solar irradiance by using two artificial neural networks: back propagation and radial basis function networks. The performance of the back propagation network is studied by using three types of data set. Then, the model accuracy is investigated by varying the number of hidden layers and training algorithms. Simulation results indicate that the back propagation network with one hidden layer with normalized data and trained by Levenberg–Marquardt algorithm outperforms the other the other studied networks. The performance of the best back propagation network is compared against the RBF network concluding to the superiority of the BP network.

In Ref. [72], authors present an intelligent maximum power point tracking method for stand-alone PV systems using artificial neural networks estimator and a fuzzy logic controller. The ANN estimate the MPP under any weather condition of solar irradiance and temperature. Then, the FLC uses the estimated MPP voltage as a reference to generate the desired PWM signal for the DC-DC converter. The obtained results using Matlab/Simulink environment proved that the performances of the proposed ANN based fuzzy MPPT technique are much better than those of the conventional IC method in terms of MPP precision and tracking speed.

In Ref. [73], authors propose a neural network maximum power point tracking algorithm. The proposed ANN-MPPT is compared to perturb and observe (P & O), incremental conductance (IC) MPPT. The simulation results carried out on Matlab/Simulink environment show the efficiency improvement as well as the oscillations reduction of the proposed ANN-MPPT compared to the P & O and IC algorithms.

In Ref. [74], authors present a novel direct adaptive neural control method for maximum power point tracking of photovoltaic systems using a DC/DC buck converter to regulate the output power. The direct adaptive neural control scheme operates on MPP and improves the performance of solar energy conversion efficiency. The online adaptation procedure is based on learning law of the delta rule where only the system output error is required. The simulation results confirm the feasibility and effectiveness of the proposed direct adaptive neural control method in transient operations and dynamic performance due to environmental conditions change. The MPP is reached very rapidly, the time response in the transient states is extremely short and the fluctuations in the steady state are considerably reduced. The results also show a great improvement of dynamic performance of the proposed method compared to the conventional perturbation and observation method.

In Ref. [75], authors investigate a detailed dynamic modeling of microgrid including PV and wind systems. The PV MPPT is realized using artificial neural network. While the control of turbine output power in high wind speeds is realized using pitch angle control technique by fuzzy logic. The PV ANN-MPPT is trained by data that are optimized by GA. The simulation results under Matlab/Simulink show that the ANN-MPPT can track the MPP under different insolation conditions and meet the load demand with less fluctuation around the MPP.

The main points of this review of application of neural networks in maximum power point tracking techniques are summarized in Table 1.

As mentioned previously, among the various proposed MPPT methods, the P & O remain one of the most used in PV systems due to its advantages compared to other methods [76–82].

3. Modeling of photovoltaic cell

Photovoltaic is the direct conversion of light into electricity. It uses materials which absorb photons of lights and release electrons charges. It can be used for making electric generators. The equivalent model of a PV cell is shown in Fig. 1 [2,11]..

The solar cell terminal current can be expressed as a function of photo-generated current, diode current and shunt current.

$$I_o = I_{ph} - I_d - I_{sh} \tag{1}$$

where

I_{ph} is the current generated by the incident light (proportional to the

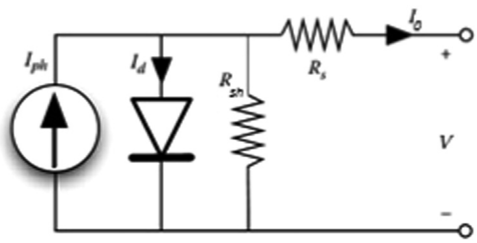


Fig. 1. Simplified equivalent circuit of a photovoltaic cell.

Sun irradiation);
I_d is the current through the diode;
I_{sh} is the current through the parallel resistor R_{sh}.

The output current of a PV array is given by following equation:

$$I_0 = N_p I_{ph} - N_p I_{rs}\left[e^{\frac{q(V+R_s I_O)}{AkTN_s}} - 1\right] - N_p \frac{q(V + R_s I_o)}{N_s R_{sh}} \tag{2}$$

where
I_{rs} is cell reverse saturation current;
q is the electron charge (1.60217646×10^{-19} C);
k is the Boltzmann constant (1.3806503×10^{-23} J/K);
n is the diode ideality constant;
Tis reference cell operating temperature (20 °C);
Vis cell output voltage (V);
A is the diode ideality constant;
N_p is the number of PV cells connected parallel;
N_s is the number of PV cells connected in series;
R_s and Rp are the series and shunt resistors of the cell, respectively.

The generated photocurrent I_{ph} is related to the solar irradiation by the following equation:

$$I_{ph} = \frac{G}{1000}(I_{sc} + k_i(T - T_r)) \tag{3}$$

where
I_{sc} is cell short circuit current at reference temperature and irradiation;.
k_i is short-circuit current temperature coefficient;.
T_r is cell reference temperature;.
G is solar irradiation in W/m^2.

4. Conventional Perturb and Observe method

As mentioned previously, photovoltaic has characterized by low efficiency and nonlinear P-V characteristics, which it presents a unique maximum power point. Therefore, tracking the maximum power point of a photovoltaic array is an essential part of a PV system. In this regards, various MPPT techniques have been developed. These methods include Perturb and observe method [7–9], incremental conductance [10–12], hill climbing [13–15], etc. In this paper, the P & O method is selected to provide the training patterns rules (data generation) required to the artificial neural network MPPT controller. The flowchart of the perturbation and observation method is illustrated in Fig. 2..

5. Proposed fixed step neural networks MPPT algorithm

Over the last few decades, artificial neural networks techniques have been considered as one of the best candidates for computational system due to the several advantages they offer compared to the conventional computational systems. Improvement in PV system performances can be achieved by adequate MPPT controllers. The emerging artificial neural networks controllers are considered to be suitable for this purpose in many papers, since they solve certain complex and ill-defined problems without accurate mathematical model where the conventional techniques have not achieved the desired speed, accuracy, or efficiency. A neural network is an information processing system [83–87]. It consists of a number of simple highly interconnected processors known as neurons similar to biological cells of the brain. These neurons are interconnected by a large number of weighted links, over which signals can pass. Each neuron receives many signals over its incoming connections, and produces a single outgoing response. Such networks have exceptional pattern recognition and learning capabilities. Recent applications of ANN have shown that they have considerable potential in overcoming the difficult tasks of data processing and interpretation. The use of ANN can be summarized by the following steps: [83–87]:

- Training patterns generation: This step constitutes an off-line computation. It consists on obtaining a set of training patterns that covers the possible operating conditions;
- Selection of inputs: This step constitutes the most important factor in the successful use of ANN and therefore needs a special attention. The state variables candidates for ANN inputs should be independent variables which have significant influence on the ANN response;
- Selection of ANN architecture: Multilayered feedforward backpropagation ANN is the most popular type used by many applications. It consists of an input layer, one or more hidden layers, and an output layer;
- Training the ANN and testing: Training is the process of determining the weights which are the key elements of an ANN. The training algorithm is used to find the weights that minimize some overall error measure such as the sum of squared errors (SSE) or mean squared errors (MSE) [83,87].

5.1. Model and training of ANN tracker

To extract the maximum power from the PV module, an ANN model with three layer feed-forward ANN is selected as shown in Fig. 3..

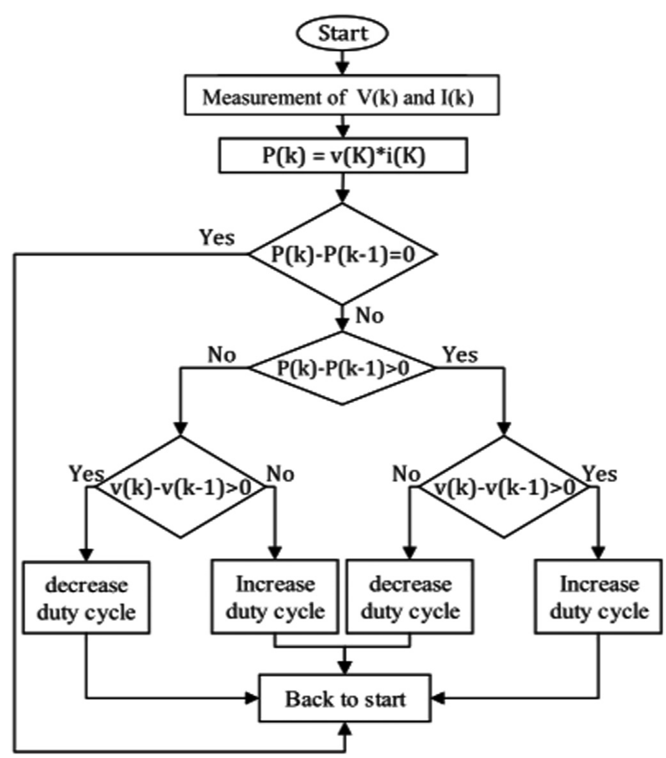


Fig. 2. Flowchart of the conventional P & O algorithm.

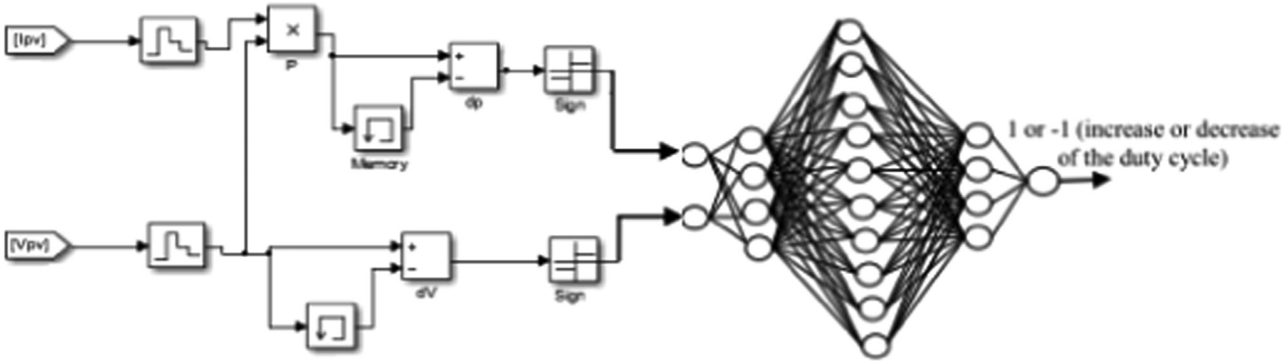


Fig. 3. The developed ANN configuration used to determine duty cycle at MPP.

The ANN inputs variables are PV array output power derivative (dP) and voltage derivate (dV) corresponding to a given solar radiation and operating cell temperature conditions. The output variable of ANN is the corresponding normalized increasing or decreasing duty cycle (+1 or −1).

In this work, a feed-forward backpropagation ANN is used with three hidden layers having a logsig, purelin and purelin activation functions, respectively. The first layer has four neurons, the second one has ten neurons and the third layer has four neurons. The output layer consists of one output neuron (Fig. 3). The optimum number of neurons in hidden layer and the number of hidden layer is determined on a heuristic basis so that the prediction accuracy is acceptable. The ANN training was performed in off-line step using back propagation algorithm. The proposed artificial neural network MPPT controller is based on the same principle of perturbation and observation method, where the decrease or increase of duty cycle depends on the sign of dP/dV. The basic principle of neural network MPPT controller is summarized in the Table 2:

The system operates in two modes:

1) **The offline mode:** required for the training of different set of neural network parameters to find the optimal neural network controller in term of structure, activation function and training algorithm;
2) **The online mode:** uses the found optimal ANN-MPPT controller to track the MPP.

5.2. Variable step size ANN-MPPT algorithms

As mentioned previously, the conventional MPPT methods based on fixed step-size have a good performance. However, they are characterized by major drawbacks like slow convergence, oscillations around the MPP and failing to track the MPP under rapidly changing atmospheric conditions. Speedy tracking can be achieved with larger step size but excessive steady state oscillations is unavoidable. While smaller step size can reduces the oscillations with slower dynamics. Solving these dilemmas, many contributions have been introduced using variable step size and significant progress has been made, where the algorithm changes the step size automatically according to the PV array characteristics. Depending on each operational condition, step size should make a satisfactory tradeoff between the dynamics and oscillations. Therefore, from the basic principle of MPPT, this study proposes a new variable step size MPPT algorithm characterized by more simplicity, faster response time and less oscillations. Fig. 4 shows the ANN-MPPT controllers developed using Simulink. The variable step-size method proposed is given as follows:

$$D(k) = D(k-1) \pm (fixed\quad Step + M*dP) \tag{4}$$

where.

D(k) and D(k−1) are the duty cycle for instants k and k-1, respectively;.

M is the scaling factor adjusted at the sampling period to regulate the step size;.

dP is the PV array output power derivate defined by dP(k) =P(k)−P(k−1).

6. Simulation results

The simulation software Matlab/Simulink is used to simulate complete simulation system architecture of our solar PV system. The Simulink model consists of the MSX-60 module connected to DC-DC boost converter drived using the ANN-MPPT controller (Fig. 5)..

Table 3 summarizes the MSX-60 module characteristics. While Fig. 6 shows the I-V and P-V characteristics..

The simulations have been carried out under fast changing irradiation. The irradiation is changed every 0.5 s from 600 W/m^2 to 1000 W/m^2 and from 1000 W/m^2 to 600 W/m^2.

Aiming to compare and adjust appropriately each algorithm according to the application, it becomes necessary to provide performance measures that can be used as comparison criteria. In this study, Beyond the typical measures of dynamic responses, we use four criteria:

- MPPT tracking accuracy;
- Response time;
- Overshoot;
- and Ripple.

6.1. Offline mode tests

As mentioned previously, this mode is required for the training of different set of neural network parameters to find the optimal ANN controller in term of structure, activation function and training algorithm. Fig. 7 shows the ANN performance in training offline mode..

6.2. Online mode tests

This mode uses the optimal ANN-MPPT controller to track the MPP using both fixed step size and variable step size ANN-MPPT controller. The simulation results for the both methods using the defined performance criteria are shown below.

Table 2
Basic principle of ANN-MPPT controller.

dP_{pv}	dV_{pv}	dP_{pv}/ dV_{pv}	Duty cycle
+1	+1	+1	D(k)= D(k−1)+step
+1	−1	−1	D(k)= D(k−1)−step
−1	+1	−1	D(k)= D(k−1)−step
−1	−1	+1	D(k)= D(k−1)+step

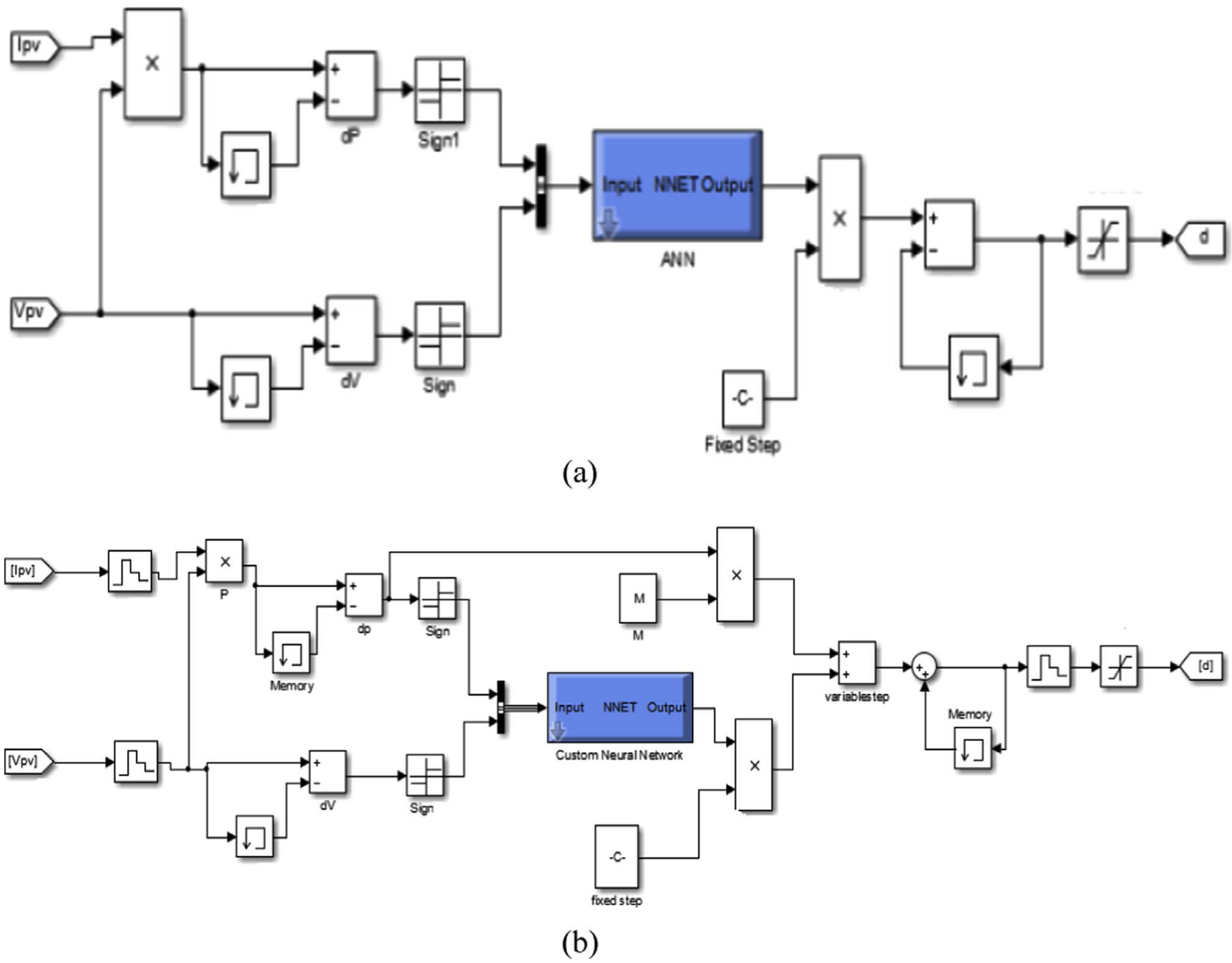


Fig. 4. ANN controller Simulink models: (a) fixed step size ANN controller, (b) variable step size ANN controller.

6.2.1. ANN-MPPT tracking accuracy

As shown in Fig. 8, both fixed and variable step size MPPT algorithms have an acceptable accuracy. The power values in both cases are very close to the theorical value corresponding to irradiation levels..

6.2.2. ANN-MPPT Response time

From Fig. 9, we can observe that response time in case of fixed step size neural network MPPT controller is 1.3x (1.3 times) the response time needed by the variable step size MPPT controller. The proposed variable step size ANN-MPPT controller takes 0.43 ms to respond to irradiation changing while the fixed step size version takes 0.56 ms. Therefore, regardless of whether the irradiation is increased or

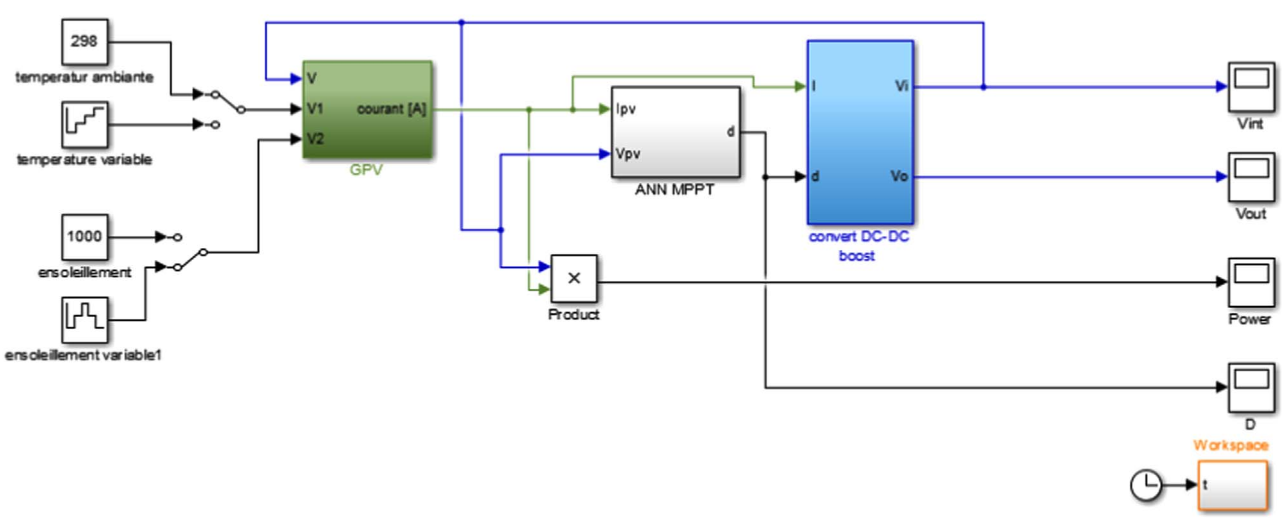
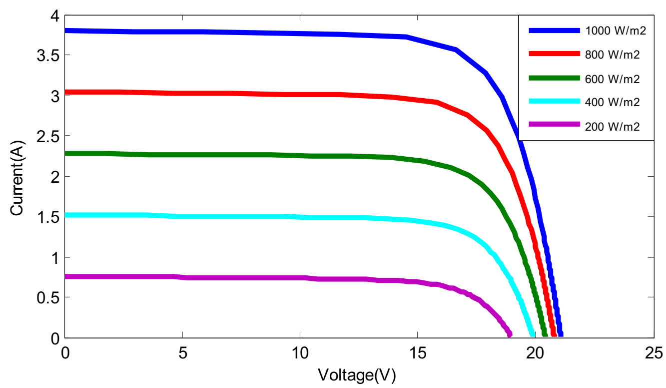


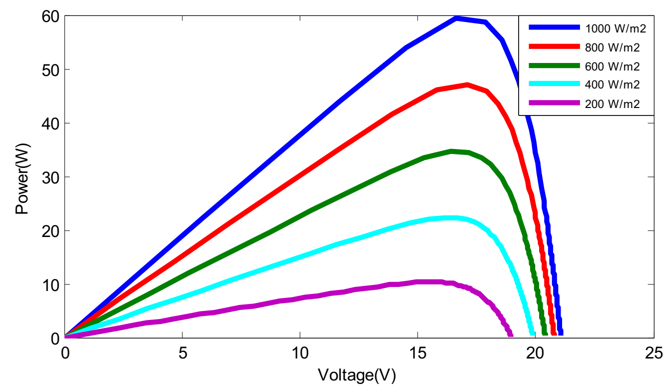
Fig. 5. Simulink model of built architecture.

Table 3
Electrical characteristics of Solarex MSX −60 (1 kW/m², 25 °C).

Description	MSX-60
Maximum Power (Pm)	60 W
Voltage Pmax (Vm)	17.1 V
Current at Pmax (Im)	3.5 A
Short Circuit current (Isc)	3.8 A
Open Circuit voltage (Voc)	21.1 V



(a)



(b)

Fig. 6. I-V and P-V characteristics under various insolation levels.

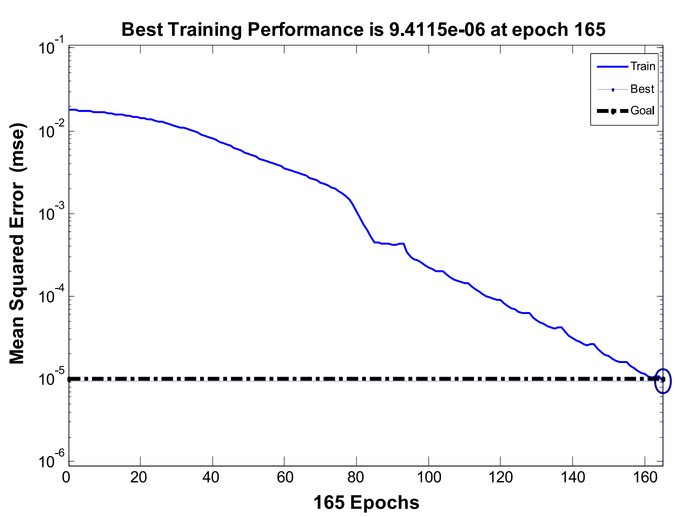
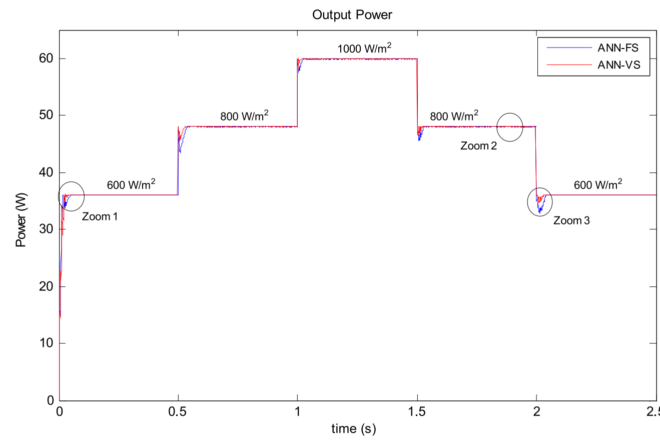
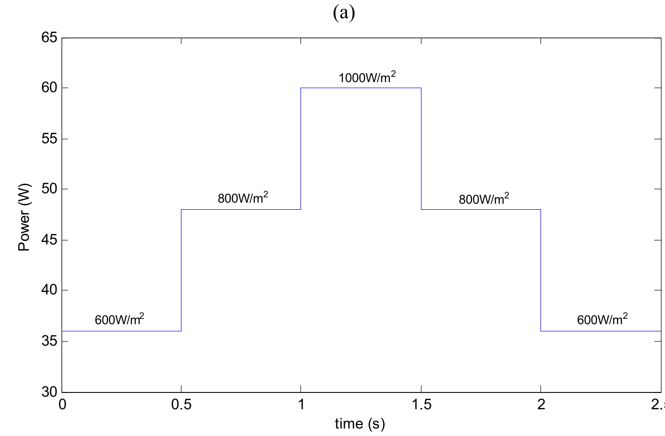


Fig. 7. Training performance of ANN-MPPT controller.

decreased, the dynamic response and steady-state power of the system are both good when using the proposed method. Between the two algorithms, the proposed variable step ANN algorithm has a good tracking rapidity especially around the MPP..



(a)



(b)

Fig. 8. ANN-MPPT tracking accuracy.

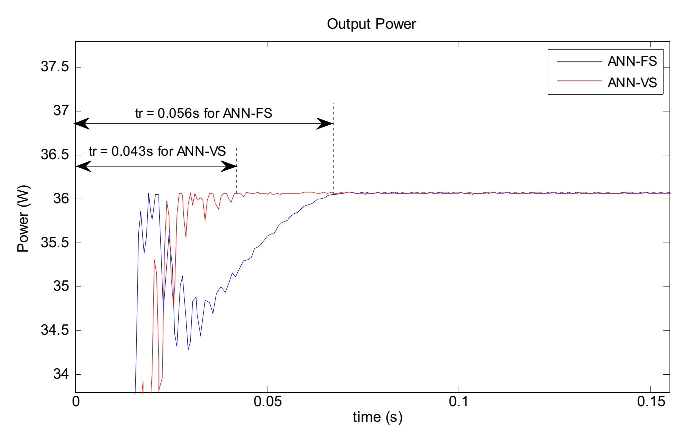


Fig. 9. ANN-MPPT response time.

6.2.3. ANN-MPPT overshoot

The overshoot in case of suddenly changing atmospheric conditions is more important with the fixed step size neural network MPPT controller compared to overshoot using the proposed variable step size neural network MPPT controller ((2.24x, 3.23 W instead of 1.44 W) Fig. 10)..

6.2.4. ANN-MPPT ripple

From Fig. 11, the improvement of variable step ANN-MPPT method regarding ripple is undeniably clear (divided per 2). It can be observed that the quality of the output power P_{PV} (regarding ripple) with variable step size neural network MPPT algorithm are obviously

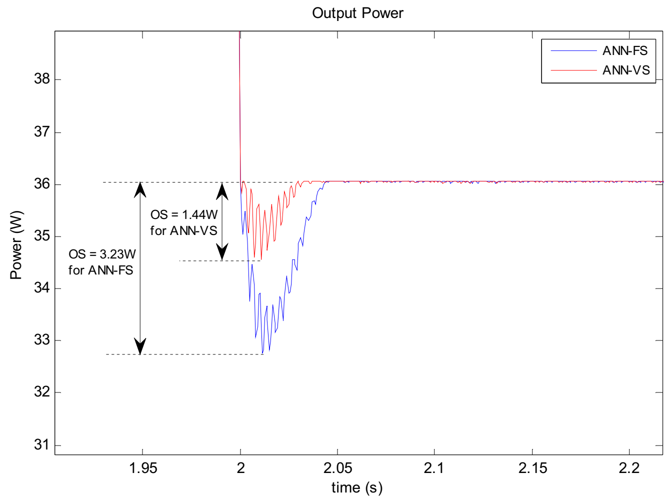


Fig. 10. ANN-MPPT power overshoot.

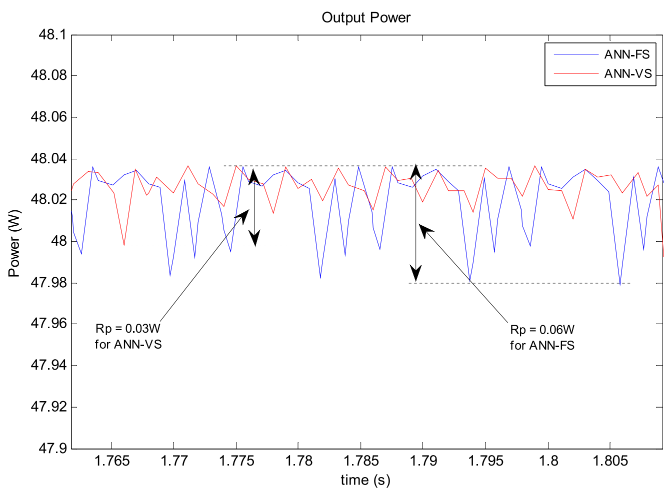


Fig. 11. ANN-MPPT power ripple.

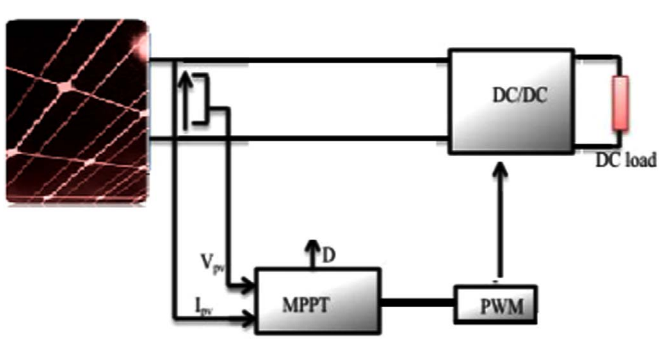


Fig. 12. Experimental PV system architecture.

better than this with fixed step size neural network MPPT algorithm..

7. Experimental results

To validate the simulations results, we implement an experimental system prototype. as shown in Fig. 12..

The experimental implemented system architecture was built using:

- four solar panels MSX-60 connected in series,
- Flyback chopper converter,
- control circuit using the dsPIC30F4011,
- several lamps as load,

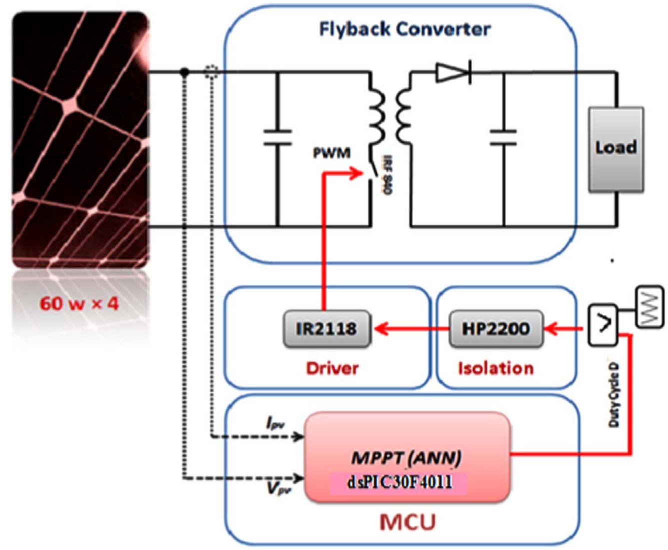


Fig. 13. Detailed experimental PV system architecture.

Table 4
Experimental setup parameters.

Parameter	Value
Sampling period: T_s	0.001 s
The fixed step size: step	0.005
The scaling factor: M	0.001

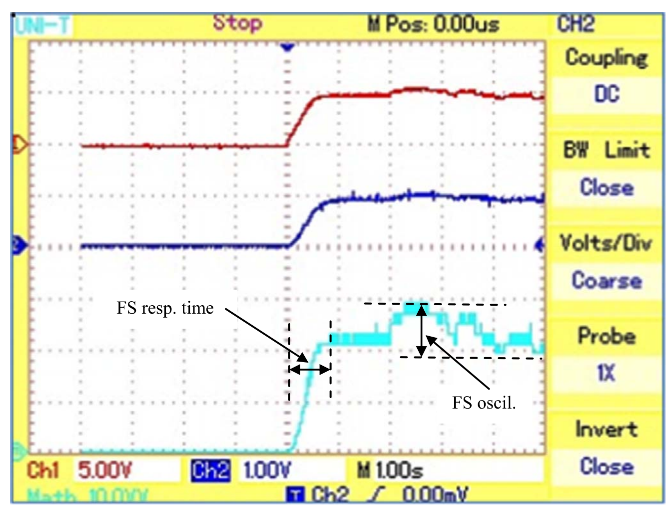


Fig. 14. PV array output performance (current, voltage and power) with fixed step size ANN-MPPT under constant insolation 800 W/m^2.

- Hall-effect sensors LA100 and LV-25,
- Oscilloscope,
- and Personal computer.

The dsPIC30F4011 was used to provide the control signals for the Flyback converter. The two Hall-effect sensors LA100 and LV-25 have been used to detect the PV output current and the PV output voltage. The detailed architecture of the proposed experimental system is given in Fig. 13..

The digital controller uses the dsPIC30F4011 to execute the MPPT algorithm and output the PWM signal. The program of the proposed variable step size neural network as well as P & O algorithms were written using the C language and were compiled by the MATLAB environment. After compiling, the program was downloaded to the

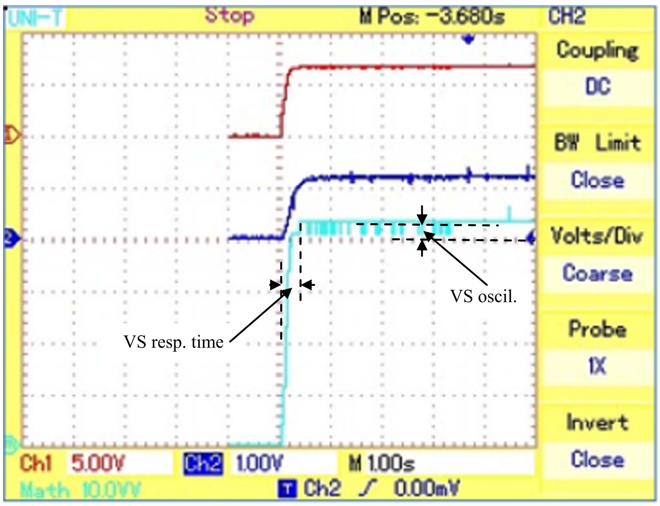


Fig. 15. PV array output performance (current, voltage and power) with variable step size ANN-MPPT under constant insolation 800 W/m^2.

dsPIC evaluation board to execute the MPPT algorithms. The analog voltage and current values of the solar PV array are fed to the 10-bit ADC module of the dsPIC to be converted into the digital values using current and voltage sensors. The PWM module of the dsPIC outputs the driving signal to the switch of the boost converter to perform the MPPT. Table 4 summarize the experimental setup parameters used in our tests.

Fig. 14 shows the MPP tracking using conventional fixed step size P & O MPPT controller. While Fig. 15 shows the MPP tracking using the proposed variable step ANN-MPPT controller…

From Figs. 14 and 15, we can see clearly the main drawback of the P & O fixed step-size method on Fig. 14. The oscillations around the MPP are visible. The improvement using the proposed algorithm are undeniably clear in Fig. 15. We have no oscillation at steady state. Moreover, the power ripple is less using the proposed variable step size algorithm compared to conventional fixed step size P & O algorithm. Therefore, the proposed ANN-MPPT controller reduce the wasting power. We can say that experimental results confirm the simulations results showing that the proposed variable step size ANN-MPPT controller outperforms the P & O fixed step size improving all performance measures.

8. Conclusions

In this paper, two new neural network MPPT controllers have been proposed, where the MPPT controllers are designed in two modes: The offline mode used for testing and optimization of neural network parameters in term of structure, number of neural layer, activation function and training algorithm; while the online mode uses the optimal ANN-MPPT controller to track the MPP. The detailed architecture and tracking method of the proposed method were discussed in simulation and real experimental environments used to verify the feasibility and functionality of the proposed method. The simulation and experimental results show that the proposed artificial neural network MPPT controller can track the MPPs quickly and accurately under different and suddenly changing atmospheric conditions. The simulations results demonstrate the high performances of variable step size neural network MPPT controller especially in term of tracking accuracy, response time, overshoot and ripple compared to the fixed step size version having the same drawbacks of P & O trainer algorithm. The experimental results confirm the simulations results showing that the proposed variable step size ANN controller outperforms the P & O fixed step size improving the convergence by eliminating the oscillations around the MPP in steady state and by the fact reducing the wasting power.

From these results, the major contribution of this work can be summarized as follows: the MPP is reached very rapidly especially in fast changing environment conditions, the response time in the transient states is improved, the overshoot and the oscillations in the steady state are extremely reduced and consequently energy losses are reduced.

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