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Research Article

Stability and Analysis of Power Quality Issues in a Photovoltaic-Based Micro Grid Using an Improved Optimized Extreme Learning Machine

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ABSTRACT

The renewable source integration in utility Grid through Micro Grids (MGs) have gained popularity in power system. In present situation the photo voltaic cell (PV), wind turbine generators and fuel cell are the is one of the major renewable sources (RES) used as generating sources in Micro Grid. In this study, maximum power point tracking error, stability and power quality issues have been improved in a PV based MG. A new Extreme Learning Machine (ELM) technique known as Ridge Extreme Learning Machine (RELM) has been investigated in order to reduce the MPPT error and to improve the dynamic oscillations. Further to achieve a robust error reduction, improved dynamics, a modified water cycle base Ridge Extreme Learning Machine (WC-RELM) is investigated using MATLAB/SIMULINK software, in this work. Finally, one of the case studies is validated in HIL, real time simulation

Keywords: Micro Grid (MG), ELM, WCA, RELM, WC-RELM

INTRODUCTION

The scarcity of conventional Energy invited renewable energy sources like solar, wind power, fuel cell and many other in to power sector. Abundant availability, less cost and superior adaptability, the PV cell is widely considered as popular alternative source [1]. The solar cell produces electricity by conversion of irradiance with association of power electronic devices. The PV cell should be operated always at its MPP level for economic generation. But in practice maximum power generation is obstructed due to nonlinearity and various atmospheric factors or weather conditions. An unique point in P-V diagram represents the maximum power generation which is called (MPPT)[2]. Many researchers have investigated the fuzzy controller to improve generation capacity of an existing MPPT [3]. The duty cycle alternation of the Boost Converter (BC), plays an important role in achieving maximum power by MPPT. For its simplicity, easy implementation the P&O MPPT algorithm popularly applied. In such MPPT control algorithm the voltage of the PV cell is maintained at neighboring region of MPP. It has low conversion efficiency due to its weather dependent nature [4]. In present scenario the design of a suitable MPPT controller, is a tough task because of system nonlinearity and environment dependent nature. Different optimization algorithms like PSO, DE, WHALO, GA with fogy logic, has been implemented in PID controller of Boost converter of the system. It is noticed that PSO based PID, MPPT controller attract the intention of Industry personals for easy execution and low strength. The authors of the paper [5] tried to improve the efficiency of the MPPT controller by the use of Artificial Bee Colony (ABC) based fuzzy controller in a standalone PV power plant. A survey in the last two decades reveals that, due to rapid market growth of Micro Grid renewable based Distribution Generations (DG) is highly required. To solve enlarged load demand, to satisfy environmental pollution policy, and the green power generation is encouraged the renewable oriented DGs with all season promised irradiant production for PV based DGs in a country like India [6]. To have economical PV power generation, Maximum power should be extracted from the solar panels, by efficient MPPT algorithm. The MPPT precision is directly affected by stability of point of common coupling (PCC). The inaccurate MPPT may provide wrong control reference to the Primary controls of MG [7]. The control order of PV-DG integration with Micro Grid, depends on primary control response to independent DG controllers (IDGCs). IDGCs are treated as the closed loop feedback path to have proper calculation of duty cycle or a

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single stage PWM reference generation (DC-AC) and in two step (hybrid) during PV (DG) integration [8-9]. There are two types of MPPT techniques such as linear & nonlinear. The P&O, Hill climbing and incremental conductance (I&C) are well established linear MPPT techniques, due to their simplicity, cost effective solutions for irradiance change [10-11], whereas during local uncertainties of PV cell like partial shading, three phase fault, these MPPT shows irregular solar data profile and erroneous maximum power extraction. Besides this the nonlinear MPPT algorithms like, Fuzzy Logic (FL), Artificial Neural Network (ANN) based on various evolutionary algorithms like PSO are effective to extract maximum power under such PV uncertainties (for example partial shading) [12]. In application of Fuzzy logic, it includes fuzzifications, decision of fuzzy rules, and defuzification for maximum power tracking, which makes the computation complex. Fuzzy rule design and selection of membership function needs earlier information of fuzzy system behavior and the fuzzy based MPPT strategy be subjected to designer's potential. Artificial Neural Network (ANN) requires verified past data for training purpose changes with PV cell. Practically ANN based MPPT control schemes are tough to calculate and these techniques depend on the system parameter. The output which is not trained well for a PV system will be inaccurate which is known as MPPT error e_{MPP}. It is proved in many research work PSO based MPPT control scheme has been performed effectively under partial shading condition with reduced accuracy with increasing randomness in solar data. PSO based MPPT is a complicated design with a large number of parameters decided by the designer. The randomness increased particles offers improved convergence to accurate maximum power and the computational burden also. To overcome these drawbacks of well-established MPPT control scheme, a simplified extreme learning machine (ELM) based MPPT controller based on WCA is applied in this paper [13-15]. To improve the capability of ELM, this work gives an idea of a learning random hidden layer feature-based ELM (RELM) with a non-iterative Moore Penrose Pseudo Inverse (MPPI) calculation. A new, small innovative process maximizes the randomized initial weights (WCA) [16]. It is natured inspired metaherustic algorithm just like swarm intelligence. The major drawback of conventional WCA is slow convergence and inaccurate optimization. To compensate these drawbacks the mutation is incorporated to make modified action of rain drops [17]. The major contribution of the paper is the water cycle optimization based RELM is investigated to improve the performance of MPPT controller, improved dynamics and compensated power quality.The paper is organized as MG architecture is presented in section-2. The water cycle algorithm and its modification with application is described in section-3. Section-4 discussed with results of the research work. The hardware validation is given in section-5. Finally, conclusion is drawn in section-6.

MICRO GRID ARCHETECTURE AND OPERATION

The three phase power is obtained from IGBT regulated voltage source converter to supply power for DG integration with PV application. As shown in Figure-1 , the single stage conversion based PV-DG is interconnected with local loadings and parallel capacitor at PCC. The historical data of solar irradiant and PV panel temperature is collected by data acquisition system (DAS) is used for MPPT scheme. The voltage source converter injects apparent power which is affected by the feedback path (PWM). The design of feedback path depends on primary control reference, that is MPPT estimation and the local measurement (PCC voltage & current). Therefore the Grid stability depends on the MPPT error. The design parameters are mentioned in the table-1.

Table 3.2: System Data

Parameters	Values
Resistance between PCC & VSC R_i	18 mΩ
Iinductance between PCC & VSC (L_i)	0.65 mH
Supply frequency (ω)	314.15 rad/sec
Resistance between PCC & Grid (R_g)	12mΩ
Inductance between PCC to Grid (L_g)	0.5mH
Capacitor of the (C_f)	0.71 mF
dc link capacitor (C_{pv})	0.6 mF

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local load conductance (g_2)	1.64 Pu
Local load susceptance (b_2)	1.0 Pu

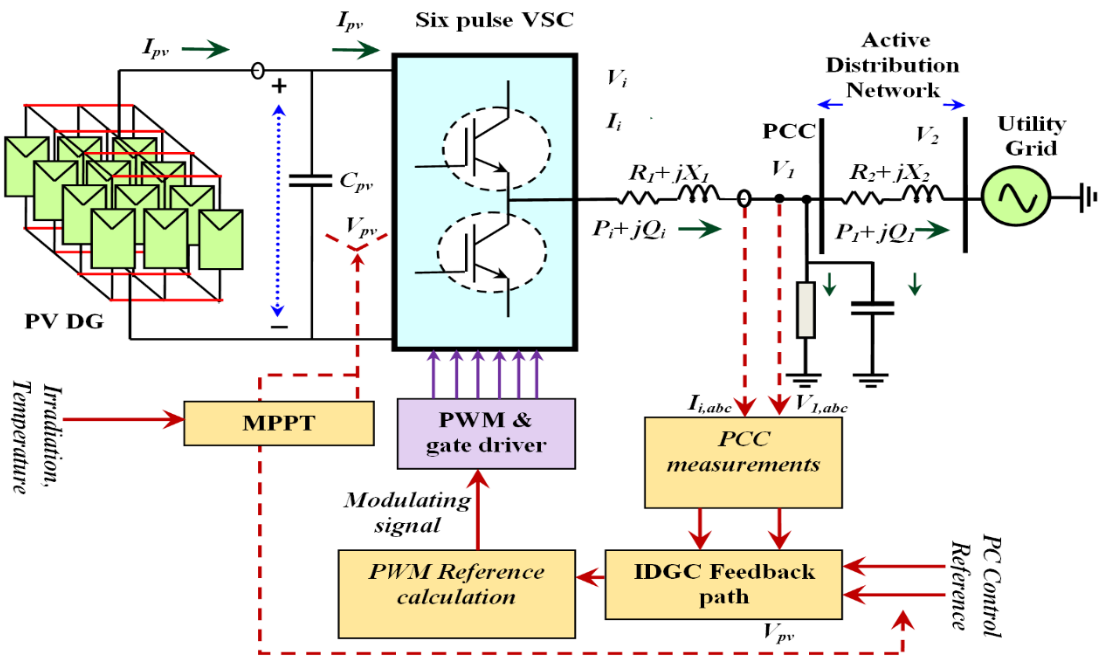

Figure 1: The Micro Grid operation with DG integration

The detailed Micro Grid distributed generators and other components are described in this section. The PV system can be described mathematically.

The MP data is created from local DGs is possible to attain while understanding the PV modeling. In the above MG structure, the six pulse VSC harvest PV voltage in a lower range and then it increases the voltage level which is supplied to PCC. The PWM reference and IDGC are designed as shown.

PV System Modeling

A single solar cell circuit is designed as a current source is taken parallel with a single diode, and resistances as shown in the Figure-2. The power loss due to leakage current is given by shunt resistance (R_{sh}) and the loss caused by the contact with metal grid is represented by (R_{se}).

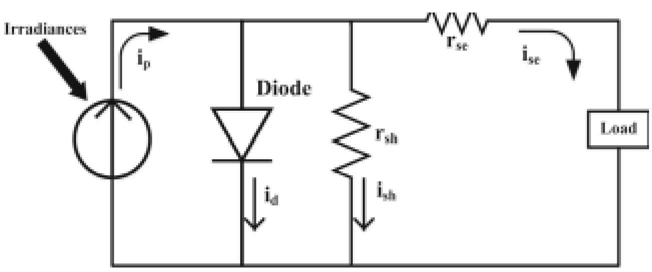

Figure 2: PV cell circuit diagram.

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A PV cell is unit of solar panel/ module. An P-N junction diode is exposed to sunlight and by photo conduction effect the light intensity is converted to electric current. The PV single diode equivalent circuit (Figure-2) is taken for considering the solar irradiance (in Watt/m2) data to calculate the PV cell parameters [14-15]. The PV cell current is represented in equation-1.

$$i_{pv} = m_{pp} \times i_{ph} - m_{pp} \times i_{rst} \left[e^{\left(\frac{1}{V_T a} \left(\frac{V_{PV} + i_{PV} R_s}{m_{se}} \right) \right)} - 1 \right] - \left(\frac{\left(m_{se} / m_{pp} \right) \times V_{PV} + i_{PV} \times R_S}{R_{sh}} \right) \quad (1)$$

where, i_{PV} → PV output current, m_{se} → modules arranged in series, and m_{pp}→modules arranged in parallel, $V_t = kT/q$ →voltage at T. Areal time solar module which consists of 46 parallel and 6 series cells with 40watt output (ELDORA-40) is designed. The parameters of the solar cell are given in table-1.

The Thermal voltage of PV cell is expressed as

$V_t = \frac{nKTN_{se}}{q}$ where n is ideality factor, K is Boltz man constant, T is the irradiance temperature and N_{se} is the series cells.

Table 1: Major descriptions of *ELDORA-40* PV at Standard Test Condition: STC (=1kW/m², 25°C)

Parameters	Values
MP Power (P_{PV})	*41W*
Voltage at MP (V_{PV})	17.48V
Current at MP (I_{PV})	*2.43A*
Short circuit current (I_{sc})	*2.67A*
Open-circuit voltage (V_{oc})	*22.1V*

CONVENTIONAL WATER CYCLE ALGORITHM

The basic idea of water cycle optimization related to natures water flow process [20]. In the process of water cycle in nature, the rain drops falls on the earth surface and created a stream which is falls in the sea. In the process some water is vaporized, condensed and reverted to earth as rain and snow. The rain drop positions are taken as control parameters. The search method continues till the optimum solutions achieved termed as sea position.

The rain drop positions are the control parameter as the design variable are given by

$$\chi = \{\gamma_1, \gamma_2 \dots\dots\dots \gamma_N\}, lb \le \gamma_i \le ub \quad (2)$$
$$i = 1,2,3,4 \dots\dots d$$

Initially rain drops presented as populations by the following positions.

$$\begin{bmatrix} \chi^1 \\ . \\ \chi^N \end{bmatrix} = \begin{bmatrix} \chi^1 & \dots & \chi_N^1 \\ .. & .. & .. \\ \chi_1^N & .. & \chi_N^N \end{bmatrix} \quad (3)$$

Where'd' is size of population and χ_i is the positions of rain drops and $i = 1,2,3 \dots d$.

The position of rain drops are generated randomly as χ^i, i=1, 2, 3, 4...d,

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$\chi^i = l_{bound} + \left(u_{bound} - l_{bound}\right) \times rand(1,d)$, Hence the method involves the control parameter by reducing the tracking error, $\varepsilon = \omega_{desired} - \omega$.

The multi objective minimized cost function is given as following

$$\psi\left(\chi^i\right) = f\left(\varepsilon_1, t\right) + f\left(\varepsilon_2, t\right) \tag{4}$$

The ψ is calculated using the Micro Grid shown in the figure-1. The given cost function are stored in ascending order. The number r_{sr} is the drops with minimum cost function values are to be selected as $r_r = r_{sr} - 1$.The number, r_{sr}, of the best raindrops, with minimum cost function values, are chosen to be $r_r = r_{sr} - 1$,number of rivers and the lowest cost function is sea. The remaining population $r_{st} = r - r_{sr}$, includes the stream that can flow from the rivers and to the sea.

The number of streams that can flow to the river is given by

$$S_n = \left\{ \left| \frac{\psi\left(\chi^n\right)}{\sum_{k=1}^{N_{sr}} \psi\left(\chi^K\right)} \right| \times r_{ST} \right\}, r = 1,2,\ldots\ldots\ldots\ldots\ldots\ldots, r_{ST} \tag{5}$$

The position of streams flowing towards the rivers and sea are given by

$$\gamma_{str}(p+1) = \gamma_{str}(p) + rand * \lambda\left(\gamma_{riv}(p) - \gamma_{str}(p)\right)$$
$$\gamma_{riv}(p+1) = \gamma_{riv}(p) + rand * \lambda\left(\gamma_{sea}(p) - \chi_{riv}(p)\right)$$

Where 'p' is the iteration count, $rand \in [01]$ and λ is constant

The cost value for new position is accepted as per the equation (*).In case the river cost is greater than the stream cost, there position will be exchanged. The same method also will be followed for their positions. To overcome the rapid convergence and trapped into local optima the river/sea water is evaporated [20, 21].

The method satisfies the following condition
If $\left|\chi_c^i - \chi_{riv}^i\right| < d_{\max}$ then vaporisation and raining stops.
$i = 1,2,3\ldots\ldots..(N_{sr} - 1)$ and $d_{\max}$ is a small number.

When the river is closed to sea and the distance is less than $d_{\max}$ then the river falls in the sea. Now evaporation happens. After long evaporation, the training is realized in nature.

The maximum distance for reduced search is given by

$$d_{\max}(k+1) = d_{\max}(k) - \frac{d_{\max}(k)}{\max\_iter} \tag{6}$$

Where 'k' is the iteration count =1, 2, 3...max_iter.

The remaining process continues by producing a fresh raindrop for stream positions as following

$$\chi_{str}^{new} = lb + (ub - lb) \times rand(1,d) \tag{7}$$

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The MPPT Scheme & the Suggested Method

The MPPT scheme like P& O are efficient in computation but during PV parameters change, the MPPT error e_{MPP} increases sharply, making the scheme erroneous. However, the nonlinear MPPT controllers like Fuzzy, ANN are giving tedious computation and performs well in PV operational uncertainties like partial shading condition. The traditional MPPTs with ANN are complex in computation due to their structure (hidden layers, input layers, neurons...) and training of DAS based irradiance. In order to reduce this computational complexity and MPPT error, RELM based MPPT scheme is proposed in this work. The irradiance data quality is decreased due to random input weight initialization. The modified water cycle algorithm is applied in RELM based MPPT to make robust operation.

The ELM is a generalized architecture like ANN which have input layer (ip), hidden layer (hd) and output layer (op). In conventional ELM, the (op) weights are determined mathematically whereas ip and bias weights are chosen arbitrary. The computational speed in ELM can be increased by MPPI training and it performs better as compared to support vector machine (SVM) [19]. The Generalized ELM construction is presented in Figure-3. The solar irradiance $(G_{pv} w/m^2)$ and PV panel temperature $(T_{pv} w/m^2)$ are selected as two input nodes in the proposed ELM configuration. The (op) nodes include V_{pv} and power P_{pv}. The dimensions of data is consists of be 'm' numbers of IP, 'n'op nodes and 's' h_d nodes. The IP nodes are presented as

$\left[\psi_{ip}\right]_{1\times M^k} = \left[\psi^k_{1ip}, \psi^k_{2ip}, \ldots\ldots \psi^k_{mip}\right]$ and the output node is designed as $[T_{OP}]_{1\times N}{}^K = [t_{1,OP}{}^K, t_{2,OP}{}^K, \ldots\ t_{N,OP}{}^K]$.

The hd output is given by

$$hd_j^K = \sinh\left(\sum_{m=1}^{M}\left(\phi_m^j \chi_m^K\right) + \lambda_m\right) \tag{8}$$

Where $[\phi]_{M\times S} \rightarrow IP$ weights (0 to 1), $[\lambda]_{1\times S} \rightarrow$bias at IP. The sine hyperbolic function is the activation function.

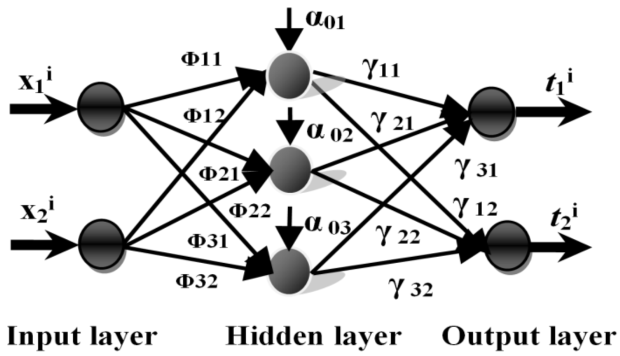

Figure 3: The generalized ELM structure

In 'k' instant the op vector is estimated to be
$[E_{OP}]^K = [e_{1,OP}{}^K, e_{2,OP}{}^K, \ldots\ e_{N,OP}{}^K]$, and the output weights are: $[\gamma]_{S\times N}$.

The desired MPPT is achieved from least square method during training of ELM is given by (9).

$$\left[T_{OP}\right]^K_{1\times N} = \left[hd\right]^K_{1\times S} \times \left[\gamma\right]^K_{S\times N} \tag{9}$$

The training now aims to be completed with no iterative computation with 'hd' as a non-square matrix. The op layer weights with MPPI, given by $\left[\eta\right]^K_{S\times N} = \left[\left(h_d{}^T \times h_d\right)^{-1} h_d{}^T\right]^K_{S\times 1} \times \left[E_{OP}\right]^K_{1\times N}$

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(10)

The minimized loss function is given by

$$J_{loss} = \|Hd - E_{OP}\| \tag{11}$$

IP weights are assumed to be random, and it affects the γ estimation. To reduce the loss a ridge regression method is applied.

constant ζ known as regularization constant is united with the hidden layer singular matrix $(Hd^T \times Hd)^{-1}$. Thus, the new method improves the loss function as given below.

$$J_{loss} = \|Hd - E_{OP}\|^2 + \frac{1}{\tau}\|\gamma\|^2 \tag{12}$$

With the above new loss function the OP minimizes with less randomness effect as based on the following MPPI theory.

$$\eta_{S\times N}^{K} = \left[\left(hd^T \times hd + \frac{I}{\tau}\right)^{-1} hd^T\right]_{S\times 1}^{K} \times \left[E_{OP}\right]_{1\times N}^{K} \tag{13}$$

Now the target T_{OP} is estimated as:

$$\left[T_{OP}\right]_{1\times N}^{K} = \left[hd\right]_{1\times S}^{K} \times \left[\left[\gamma\right]_{S\times N}^{K} = \left[\left(hd^T \times hd + \frac{I}{\tau}\right)^{-1} hd^T\right]_{S\times 1}^{K} \times \left[E_{OP}\right]_{1\times N}^{K}\right]_{S\times N}^{K} \tag{14}$$

Since IP and bias weights, initialized randomly, the MPP error does not reduce effectively, under uncertainties like irradiant change and partial shadings. Thus, an improved water cycle optimization is introduced for proper tuning of IP weights.

IP Weight Enhancement by Improved WC

In this algorithm the basic idea depends on water flow. Where the evaporation, transpiration, condensation, precipitation and runoff take place to reach a raindrop to sea (optimal point). The rain drops acts as population which is initially randomly created.

For minimum MPP error the cost function is given in equation (15)

$$f(\phi) = \min\left(T_{OP}^{K} - E_{OP}^{K} \big/ N\right) \quad \text{where } N=M. \tag{15}$$

The population created from rain drops are defined as

$[Rd]_{B\times C} = [rd_1^K, rd_2^K, \ldots rd_C^K]$.

Rv, presents number of rivers and (S_E) represents the number of streams towards sea. The streams (Str) are expressed as:

$$\underset{k=1\,\text{to}\,SE}{Str} = round\left(\left|\frac{CG^k}{\sum CG^k}\right| \times Str\right), CG^k = f(\phi)^k - f(\phi)^{SE+1} \tag{16}$$

The stream changes with each generation 'k' and approaches to S_E.

The stream position can be improved by inserting chaos signal as in (17)

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$$\underset{(i=1\text{to } S_E)}{k_{str}^{i}(\mathrm{t}+1)} = k_{str}^{i}(\mathrm{t}) + Chao\ (\mathrm{t}) \times \left(K_{SE}(\mathrm{t}) - K_{str}(\mathrm{t})\right) \qquad (17)$$

Thus, the evaporation including chaos signal is given by:

$$\left\| k_{SE} - \underset{(i=1 \text{ to } R_v)}{k_{Rv}{}^{i}} \right\| < Chao(\mathrm{t})$$

$$\text{or } \left\| k_{SE} - \underset{(j=1 \text{ to } Str_t)}{K_{Str}{}^{j}} \right\| < Chao(\mathrm{t}) \text{ or } Chao(\mathrm{t}) < 0.1 \qquad (18)$$

At last, the process reached at the optimal solution of equation (9), the total generation.
The proposed MPPT performance is noticed from MPP error. The standard MPP errors are mentioned below.

$$MAPE = \left[\frac{1}{N} \sum_{k=1}^{N} \frac{|T_{OP} - E_{OP}|}{T_{OP}} \right] \times 100$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^{N} |T_{OP} - E_{OP}|^2} \qquad (19)$$

MAPE is mean absolute percentage error and RMSE is root mean square error.

RESULT DISCUSSION

Case-1: MPPT Error Minimization

From the DAS data validation and the PCC of Micro Grid parameters, the performance of the proposed MPPT is judged. The DAS data with 5 minutes interval measures various error responses such as RMSE, MAPE. For long time interval the MPP will be erroneous for which 5 minutes interval is considered. Here the proposed modified WC-RELM has been implemented to estimate maximum power in a Micro Grid. It's performance is compared with basic ELM, RELM as shown in Figure-2. The entire PV data is classified into different seasons and here only summer data profile is validated. Figure-3 and Figure-4 depicts RMSE 0.061% - 0.88% and MAPE 2.48%-4.48%. The RMSE of ELM and RELM are given in Pu 0.032-0.0038 respectivelly.The rane of MAPEs in Pu are 0.0412-0.0622 and 0.1053-0.2348 conventional RELM and ELM respectively. It is evidently proved that WC-RELM based MPPT performs effectively better than the conventional ELM.

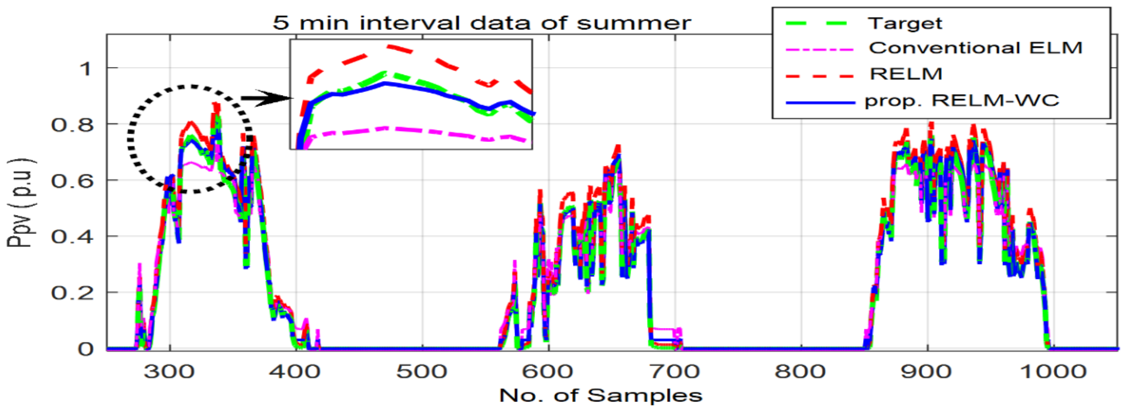

Figure 2: Performance of proposed RELM-WC MPPT through PV power

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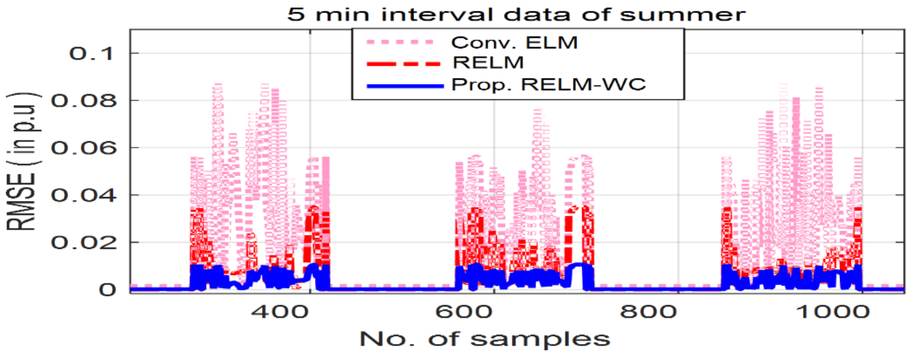

Figure 3: Performance of proposed RELM-WC MPPT through RMSE

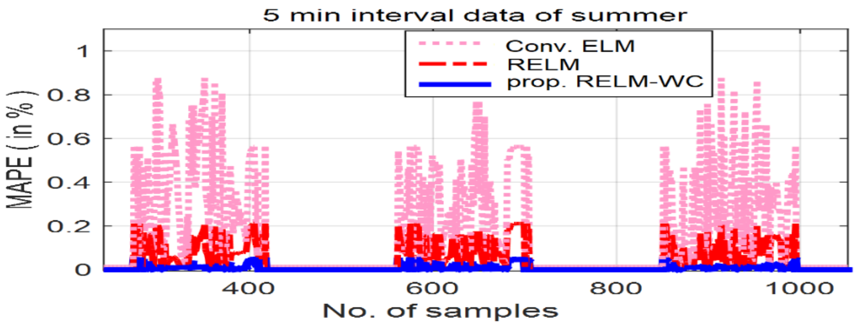

Figure 4: Performance of proposed RELM-WC MPPT through MAPE

Case-2: Performance of MPPT with DG integration:

The DG integration with AC Micro Grid is most challenging task in Micro Grid Control. The MPPT error affects the contro hirarchy such as PC, IDGC etc. The Grid stability fails under maximum power estimation. The parameters of PCC such as power (P), frequency(f) is calculated with the proposed scheme, RELM-WC and the results are compared with basic ELM. The sysstem is simulated for 10 second and a disturbance is created for 2.5 second. Figures-4 to Figure-7, voltage, power & frequency evidenced with coordination to IDGC is evidenced in terms PCC response as in. From the figures it is depicted that the proposed scheme performs far better than the basic ELM.

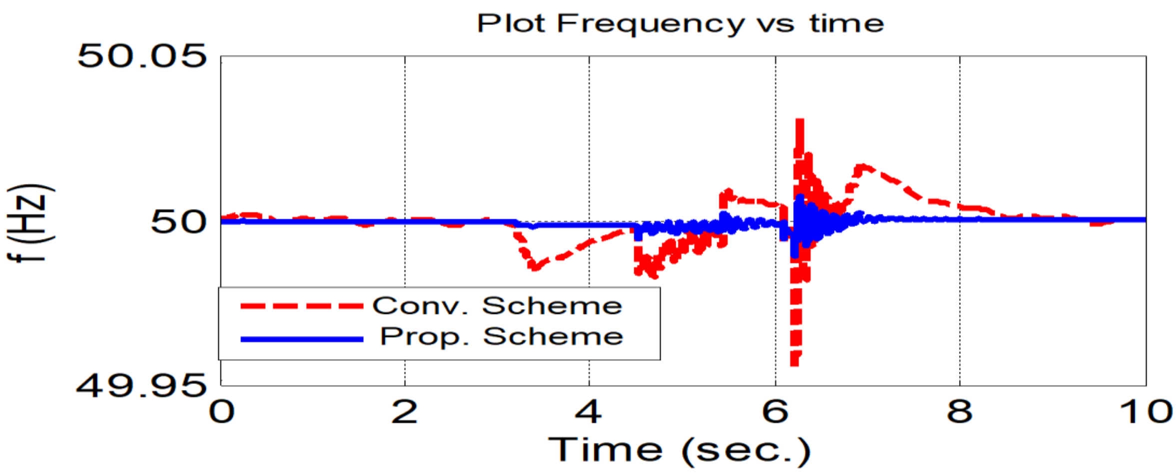

Figure 5: Performance of proposed RELM-WC MPPT through frequency deviation

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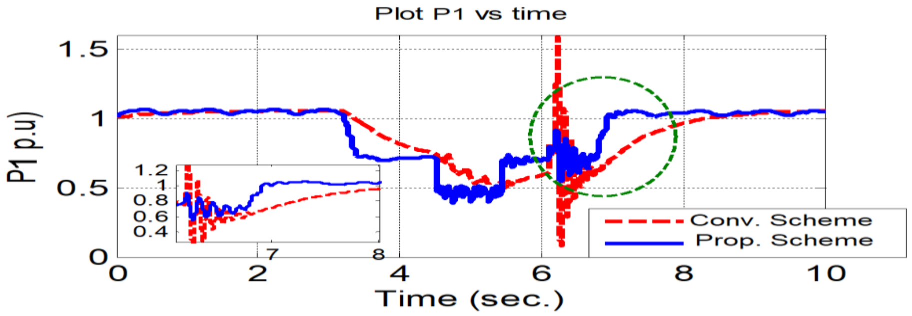

Figure 6: Performance of proposed RELM-WC MPPT through Real power

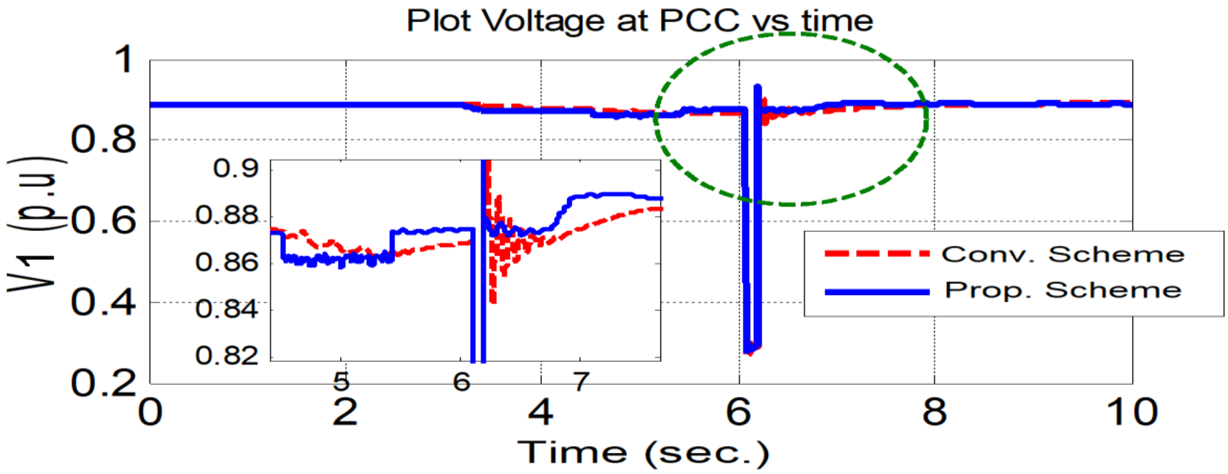

Figure 7: Performance of proposed RELM-WC MPPT through PCC voltage

The tough Grid operation with instant contingency, the Micro Grid is simulated. During time interval 4.55 sec to 6.45 sec, the PV cell is subjected to partial shading condition with reduced irradiation. Simultaneously a fault is created at bus-1, with duration of 0.1 second (6.1 to 6.2 second). To justify the primary control accuracy of the said MPPT scheme and the disturbance is evidenced with 14-18 cycle. But the conventional ELM reduces the MG stability (40-50 cycles), due to erroneous reference. In order to overcome these errors, it is found that the proposed WC-RELM is highly suitable for PV-DG integration in MG application. As depicted in Figure-5 to Figure-7, the proposed MPPT scheme performs effectively better than the conventional ELM, under various MG contingencies. The various disturbances like irradiant change, partial shading and three phase fault, the number of cycles is considered as performance index.

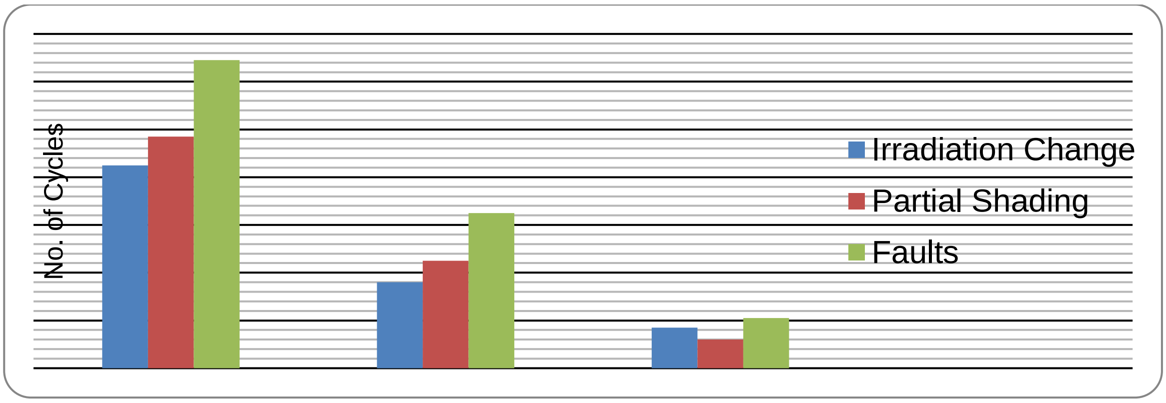

Figure 8: Comparision of performanc indices.

Case-3: Power Quality Compensation by Proposed RELM-WC MPPT

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Many of the power quality signals in the proposed Micro Grid, is simulated in MATLAB SIMULINK platform. Voltage sag is created by a three phase fault of duration 0.1 second.as shown in figure-9. Here in this work a heavy three phase load is switched on to have voltage swell analysis with the proposed controllers as depicted in fig-10. The voltage sag and swell has been improved by the proposed controller as shown Figure-9 and figure-10 respectively. The harmonics improvement is presented in figure-11. The power quality of mixed disturbed signals like voltage sag+ harmonics and voltage swell+ harmonics are depicted in the figure-12 and figure-13. The voltage deviation and total harmonic distortion (THD) has been improved as shown in the figure-14. The inverter current distortion has been corrected as presented in the figue-15. The oscillatory transients and flickers are caused due to switching on A capacitor of 2.25KVAR and electric furnace switching normally creates oscillatory transient and voltage flickers , as depicted in Figure-11. Phase 'a' of PCC voltage disturbed signal is removed in on-grid condition. Here 1,55,000 samples of PCC voltage signal is simulated for 0.4 second.

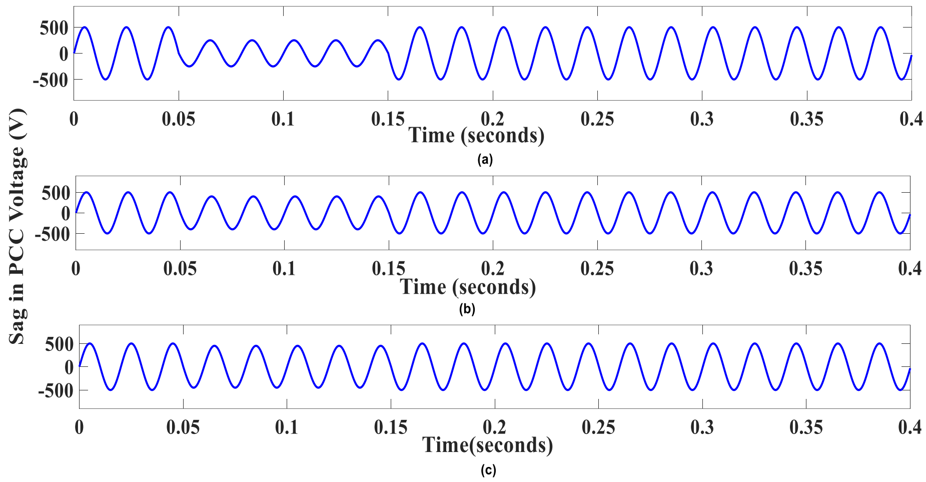

Figure 9: The voltage sag by (a) ELM (b) RELM (c) WC-RELM

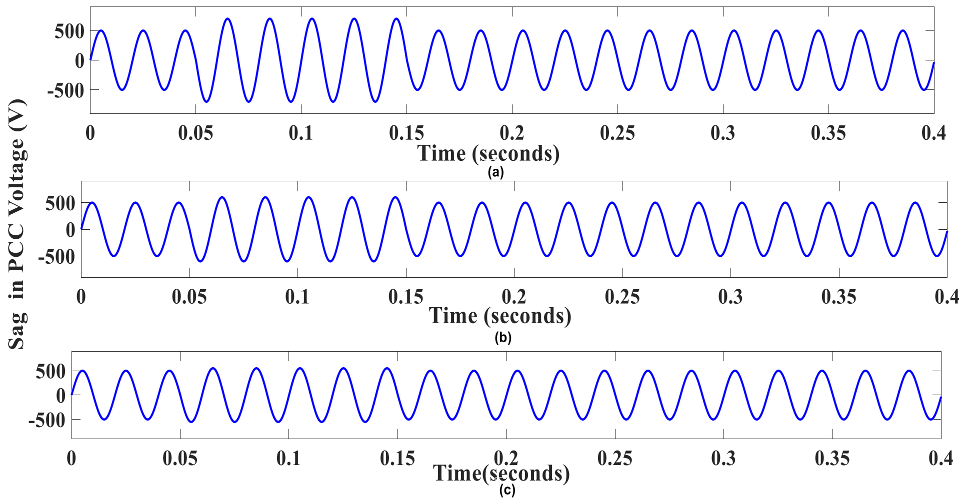

Figure 10: The voltage swell by (a) ELM (b) RELM (c) WC-RELM

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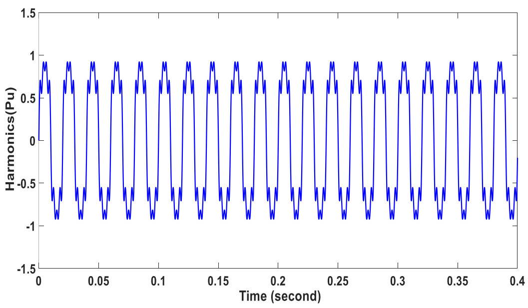
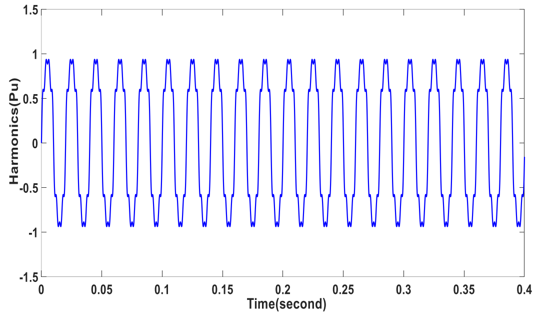
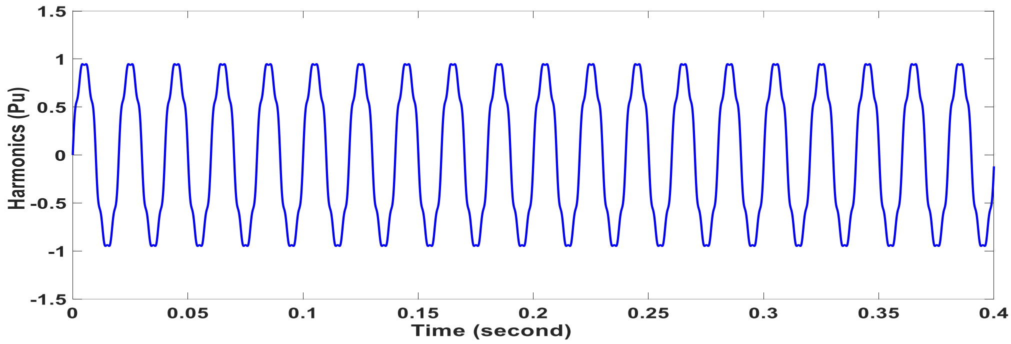


(a)

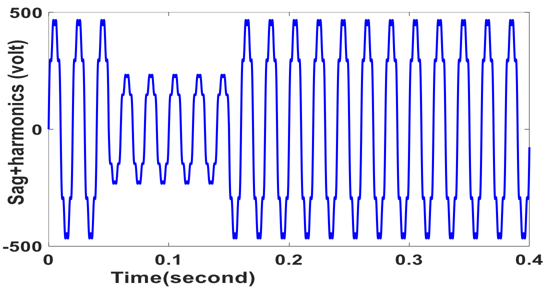


(b)

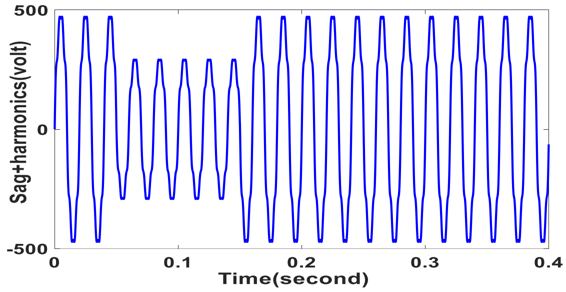


(c)

Figure 11: Power quality through harmonics Analysis by (a) ELM (b) RELM (c) WC-RELM



(a)



(b)

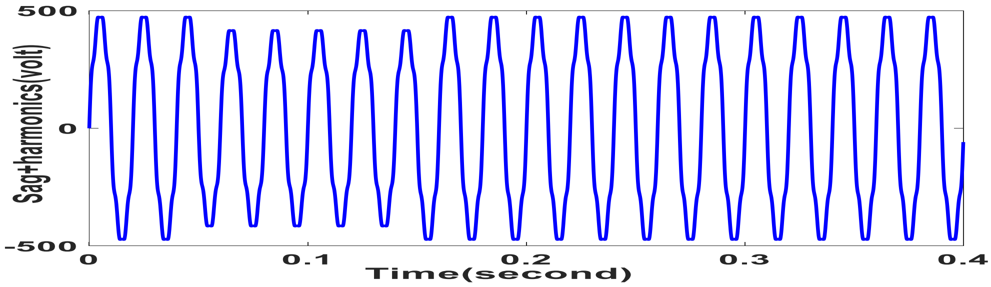


Figure 12: Power quality issues through Sag+harmonics by (a) ELM (b) RELM (c) WC-RELM

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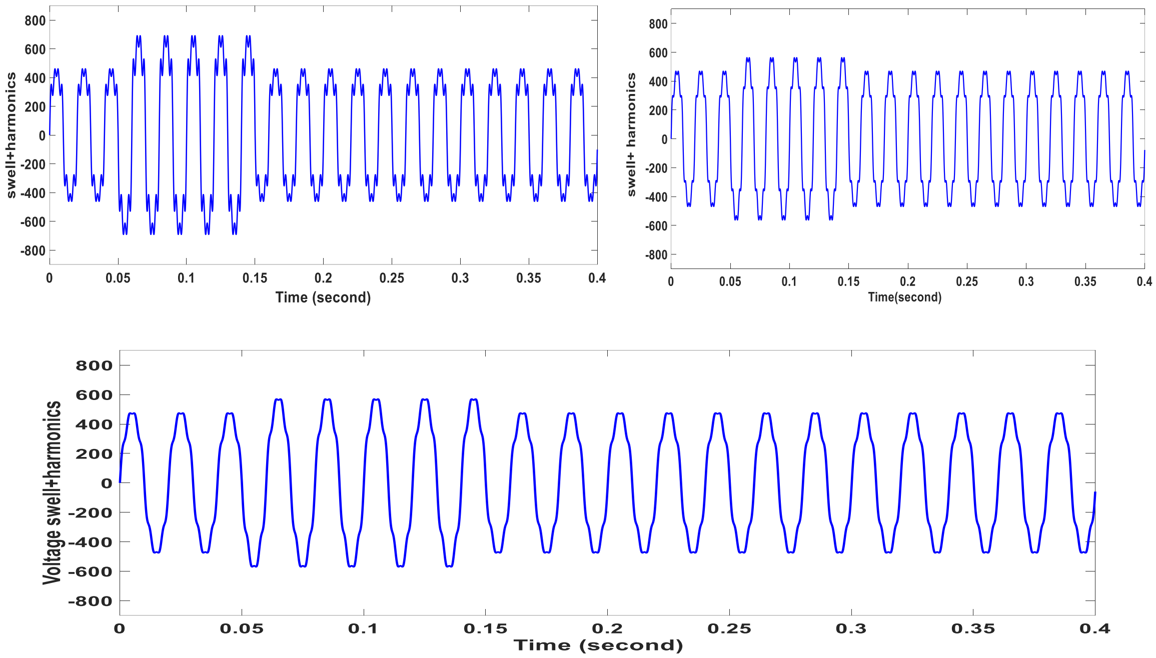
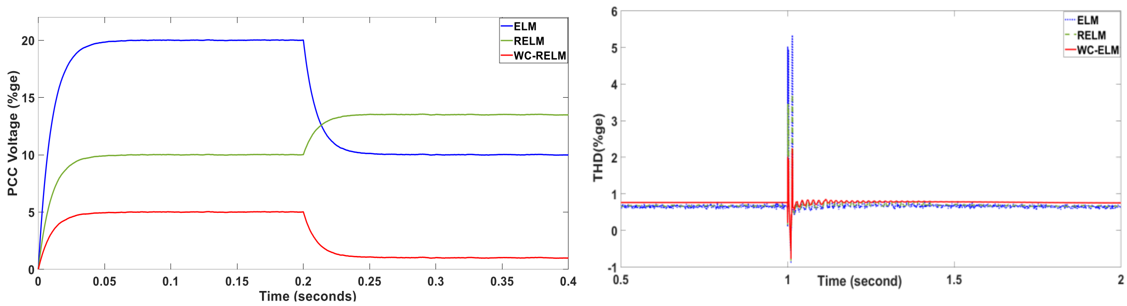
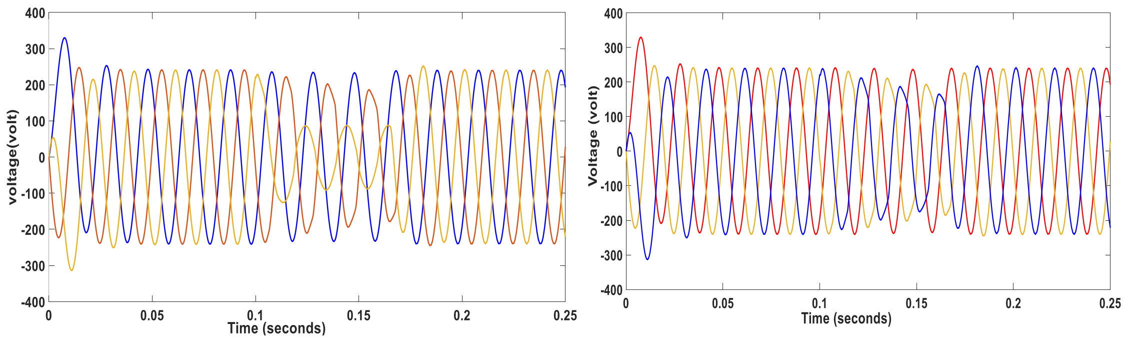


Figure 13: Power quality issues through Sag+harmonics by (a) ELM (b) RELM (c) WC-RELM



(a) (b)

Figure 14: Power quality improvement by the proposed controller through (a) Voltage deviation (vd) and (b) Total harmonic distortion.



(a) (b)

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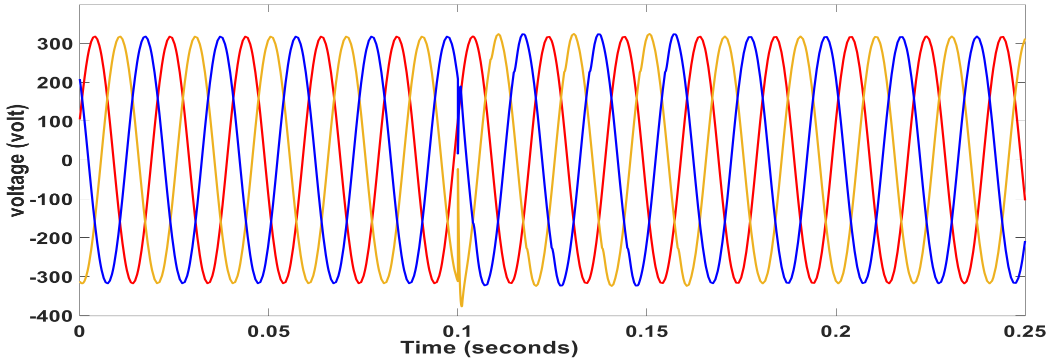


Figure 15: Power quality improvement by the proposed controller through voltage unbalancing by (a) ELM (b) RELM (c) WC-RELM

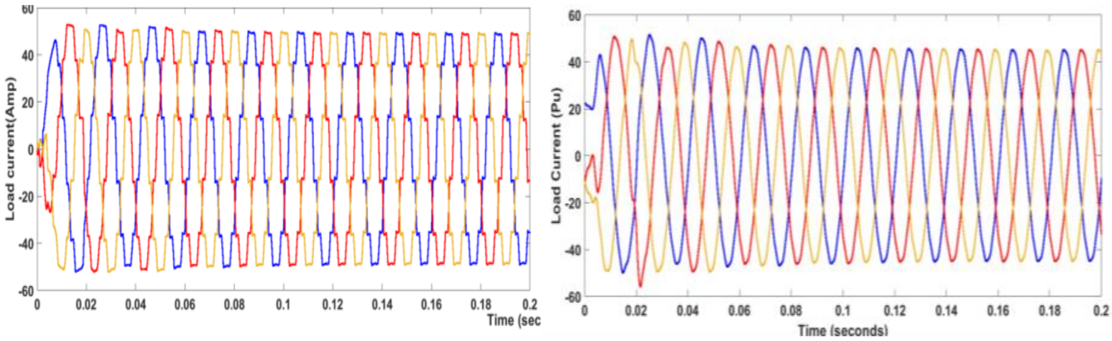
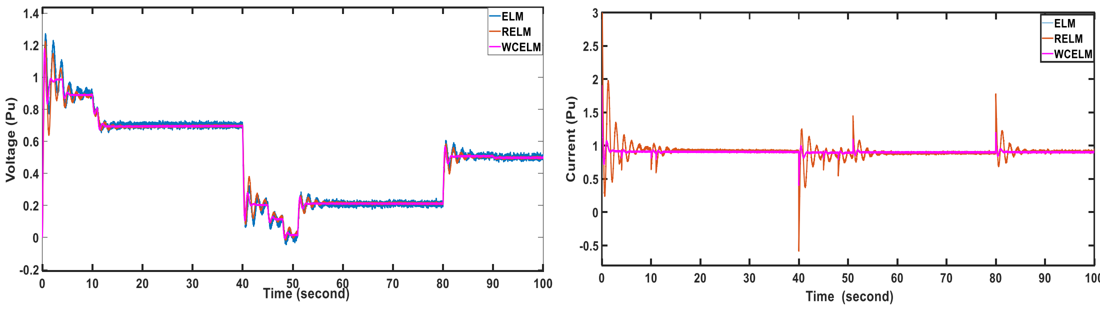


Figure 15: Power quality improvement by the proposed controller through inverter current by (a) ELM (b) WC-RELM

Case-4: Partial Shading

In this case study the partial shading is performed by short circuiting some cells in PV array at fixed time steps. The PV array. The Micro Grid instability causes due to irradiance change caused by partial shading. The MG instability is presented in Figure-16. The conventional ELM regulates the disturbance in voltage, current, real and reactive power at PCC. As depicted by the Figure-16(a) the voltage fluctuation controls in overshoot and settling time. The voltage overshoot fluctuates from 0.1 Pu to 1.2 Pu at different time intervals. The current overshoot oscillates from 0.25 Pu to 1.2 Pu. Similarly reactive power and real power fluctuations are shown in Figure-16() and 16(d). In Figure-16(d) it is described that the PV generation changes with respect to time but load do not change. In all the simulations it is noticed significantly that at t=40 sec the PCC voltage, current and power is negative. It is because the number of PV cells short circuited such that PV becomes incapable to supply the utility Grid, rather the utility Grid supplies power to the generation side. In the entire simulation it is seen that the proposed WC-RELM performs significantly in controlling the uncertainties.



(a) (b)

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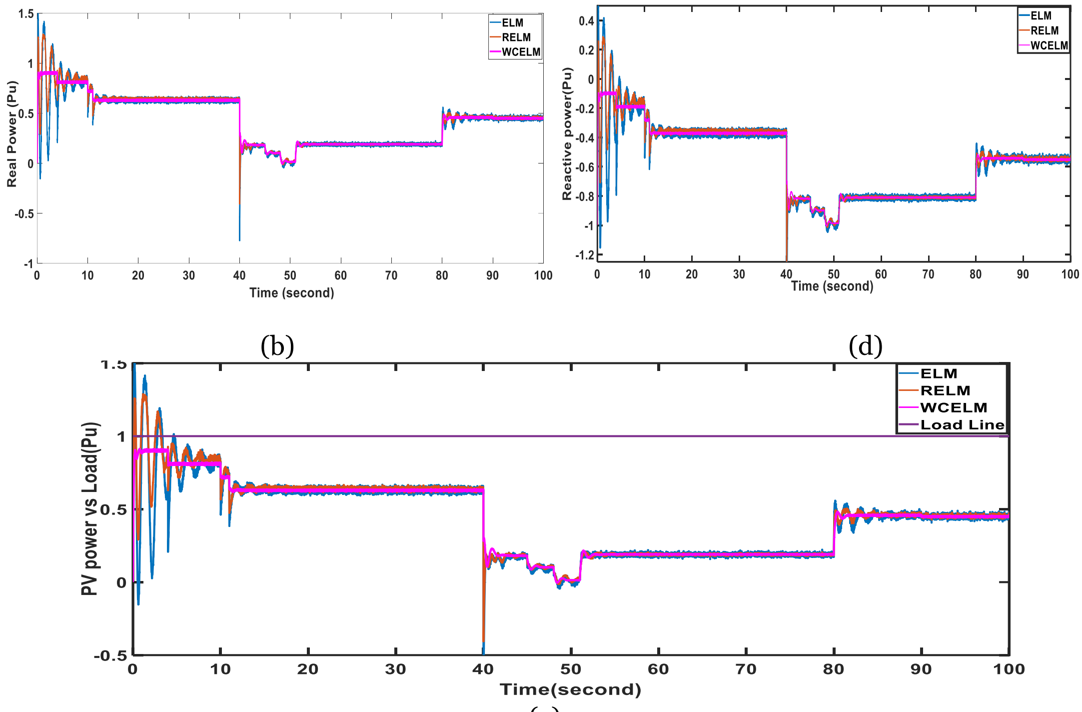

Figure 16: performance of the controllers under PV partial shading

Hardware in the Simulation (HIL)

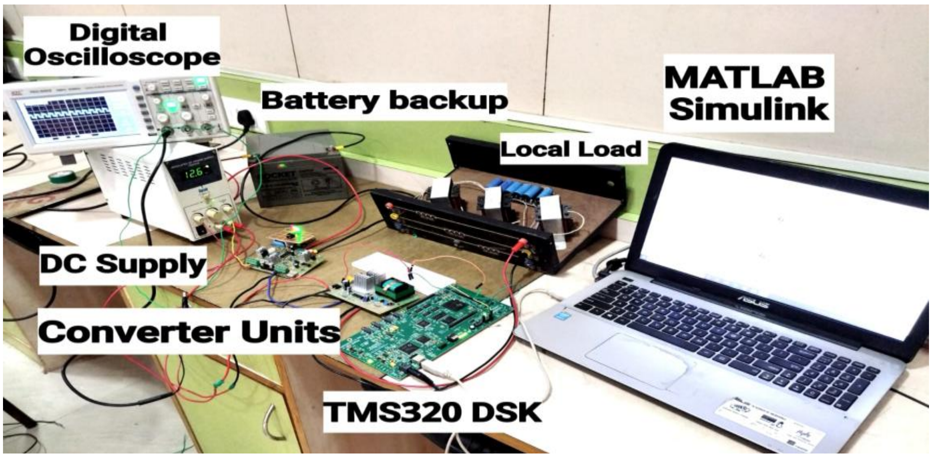

Figure 16: The Hardware setup of the DC converter of Micro-Grid

The power unbalance condition is validated with hardware simulation. The structure of various components (PV based DC/DC converter) of HIL simulation is shown in Figure 16.

To validate in real time control based on the TMS320F240 DSP R&D controller board, with 603 PC floating point processor. The running frequency is 250MHz. For improve I/O interfacing, TMS320F240 DSP microcontroller is included to supervise Micro Grid. Here a lab box is an interfacing device board has a numerical subsystem to control the µ-Grid, as is based on the TMS320F240 DSP microcontroller, for advanced I/O applications.

The TMS320F240 DSP Controller Board connects to via the (CLP1104 Connector/LED combo Panel). With the devices to be communicated to the processor in which an array of LED to indicate the digital signal state. The RTI software is used for conversion of Simulink to real time simulation. The control algorithm is written in MATLAB /SIMULINK and it was implemented on in TMS320F240 DSP board. Here the control version 3.5 is used. The features allow the hardware signals from I/O signals.

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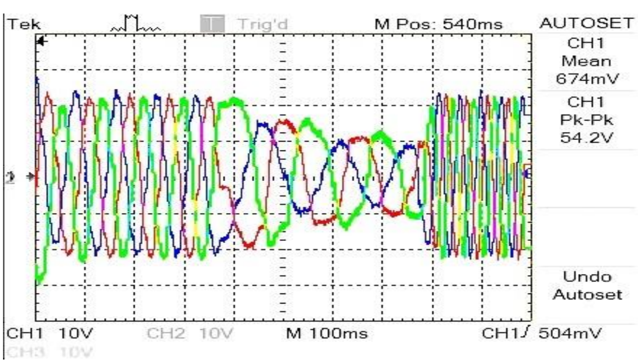

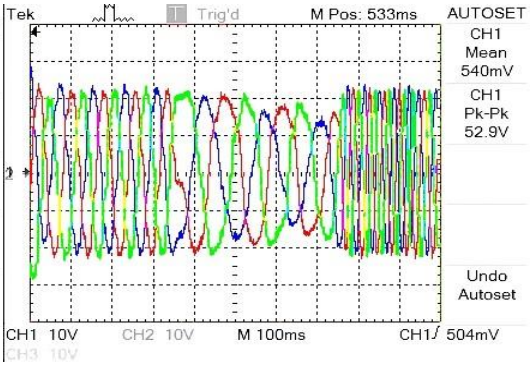

Figure 16: PCC unbalanced voltage with ELM,validated with HIL

Figure 17: PCC unbalanced voltage with RELM validated with HIL

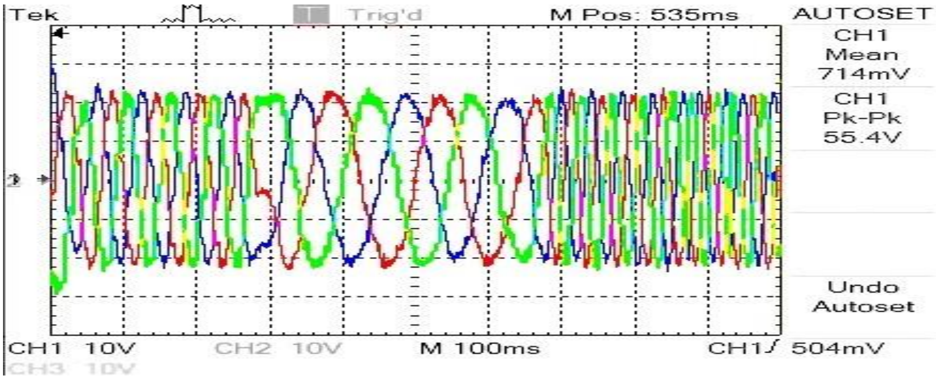

Figure 18: PCC voltage balanced with WC-RELM validated in HIL

CONCLUSION

In this paper a new extreme learning Machine (ELM) based MPPT technique is presented to improve the stability margin and to reduce the MPPT error in a PV based Micro Grid. Besides this the various power quality issues also have been improved in such a active network. The linear and nonlinear conventional MPPT techniques like, P&O, Hill climbing, ANN and Fuzzy logic based MPPT, have different drawbacks in tracking accurate MP under parametric uncertainties such as partial shading and irradiance change. To eliminate the above drawbacks and to achieve an accurate and speed MP tracker, a new (RELM) is investigated in a PV based Micro Grid with minimum MPPT error.

This is achieved by decreasing the arbitrariness of the IP weights. With application of improved water cycle based (WC) best weight collection. The improved water cycle is presented with confused recording rain drops in flow of water stream towards river or sea. The efficiency of the proposed MPPT is validated with standard error formulation (RMSE, MAPE). Through Grid controllers like PC, IDGC PWM based PLL, the proposed WC-RELM is validated showing the Grid stability improvement and power quality issues, in terms of dynamic oscillations at PCC of the Micro Grid. The investigation study of the planned MPPT technique used MATLAB/SIMULIK software. Then one case study (unbalance condition) is confirmed in real time simulation using HIL. However, the optimization techniques are not the final method to justify the best improvement in MPPT performance. Thus, various improved ELM, auto encoder based, deep learning based MPPT controller may be studied in future research.

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