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EFFICIENCY COMPARISON BETWEEN DIFFERENT ALGORITHMS FOR MAXIMUM POWER POINT TRACKER OF A SOLAR SYSTEM

[1]Md. Hasibur Rahman, [2]Swadesh Poddar, [3]Mohammad Mahbubur Rahman Khan Mamun, [4]Selim Mahmud and [5]Md. Tanvir Yeasin

E-mail: md.rahman.hasib@gmail.com

Abstract: There are several maximum power point tracking algorithms available such as Perturb and Observe, Incremental and Conductance, Current Sweep and Constant Voltage method etc. Here we'll discuss few new techniques based on FL, Stimulated Annealing and Particle Swarm Optimization. And will show a comparative study with Genetic Algorithm. These techniques are as simple as the conventional one, mentioned above and yet these can successfully encounter the oscillation problem and steady state error even under adverse environment with more than 98.5% efficiency. These ideas will simplify the hardware complexity through the help of programmable microcontrollers

I. Induction

Amongst the available renewable energy sources, solar energy has been proved as most useful. Usually solar panel efficiency is not higher. For this constraint, a lot of research works have been conducted on solar panel driver circuit to optimize the power output of solar panel. However, Maximum Power Point Tracker (MPPT) actually reduces the deficit between electrical power supplying capability of PV array and same to the electrical load. A handful of algorithms and techniques have been proposed for MPPT. Most commonly used techniques of MPPT are Perturb and Observe(PO), Incremental and Conductance(IC), Current Sweep, Constant Voltage method etc. along with some DSP based methods [1], [2]. PO method is simple but steady state error is large. Moreover, it has oscillation at steady state operation at the vicinity of maximum power point [1], [2]. Modified PO technique has improved convergence problem at rapidly changing weather pattern but has not improved efficiency [6], [7]. Incremental conductance has proved to be better in terms of efficiency, but one major problem is that power of solar panel is a non-linear function of duty cycle. Hence uniform step size is not a very good choice for fast settling time. PO algorithm suffers from problems in getting stuck at local minima or maxima [2], [3]. All these traditional MPPT algorithms use a fixed rigid algorithm causing difficulty to respond quickly and appropriately to changing weather pattern. But, to some extent IC has better performance in adverse weather in case of large system[10]. Hence, to improve steady state operation, Digital Signal Processing(DSP) based algorithms have been proposed which are costly and leads to complexity of hardware [9]. To improve system performance, PV array integrated MPPT algorithm has been proposed. Our proposed algorithms have encountered all the problems effectively. The efficiency is more than 98.5% with settling time less than 1ms. It has no oscillation at steady state condition if weather pattern remains same. Moreover, number of iteration reduces while jumping from one weather condition to another.

Simple micro-controller based control scheme can be applied to control the duty cycle of the buck/boost converter for maximum power transfer to load [4]. These intelligent algorithms have already shown better performance in terms of efficiency and adaptation to changing weather profile.

FL(FL), Genetic Algorithm(GA) and Particle Swarm Optimization(PSO) based algorithms are most popular amongst the much talked intelligent algorithms. FL algorithm has a fast transient response but it faces the problem of oscillating around the maximum power point even under steady state condition like traditional PO algorithm [1]. FL has a major advantage over non-intelligent algorithms that it does not fall into the trap of local maxima. In this paper a novel approach of improving FL algorithm according to objective function has been developed. However these two algorithms perform better than traditional PO algorithm. Yet there is a tradeoff between quick settling time and steady state error.

Our proposed algorithm for PSO has proved itself to be quite satisfactory than traditional MPPT algorithms considering both transient and steady state system response. A step by step procedure of physical realization of PSO algorithm [3]-[5], [14] incorporated with practical circuit configuration will be thoroughly described in this research work.

The algorithms are simulated in MATLAB and PSIM under all possible weather patterns based on the datasheet of MSX60 solar panel.

II. PV Profile

Fig. 1 shows PV criteria under different irradiance. Again V_{oc} has a reverse proportional relationship with temperature with nearly same I_{sc}, provided that irradiance remains same.

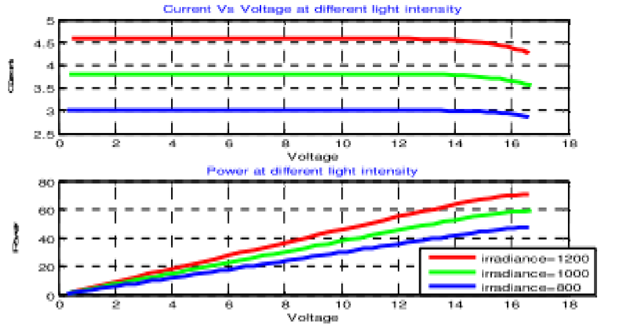

Fig. 1: Short-Circuit current(Amp) & Power(Watt) Vs Open-Circuit voltage(Volt) at varying Irradiance(Watt/meter^2)

Fig. 2 shows PV criteria under different temperature and Fig. 3 for different conditions.

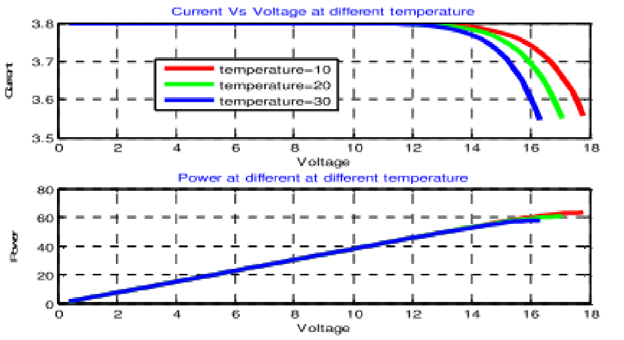

Fig. 2: Short-Circuit current(Amp) & Power(Watt) Vs Open-Circuit voltage(Volt) at varying Temperature(^{0}C)

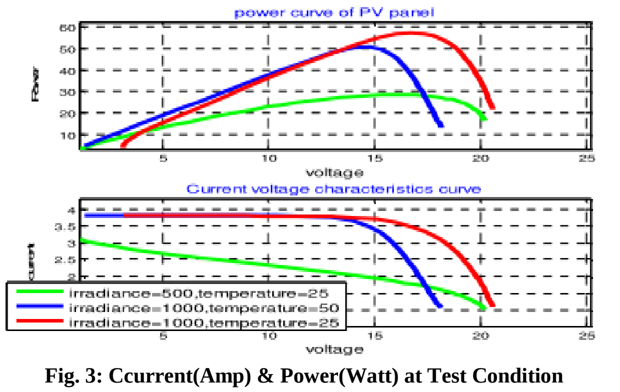

Fig. 3: Ccurrent(Amp) & Power(Watt) at Test Condition

These curves have been generated by simulation of MSX 60 solar panel from renewable energy TOOLBOX using PSIM.

III. Algorithm for Stimulated Annealing(SA)

'Annealing' is actually a thermodynamics term [12]. If a solid is heated past melting point and then cooled, the structural properties of the solid depend on the rate of cooling. If the liquid is cooled slowly enough large crystals will form. However, if the liquid is cooled quickly the crystals will contain imperfections. Thus crystal formation using intense heating and slow cooling is termed as stimulated annealing. This phenomenon can be explained more precisely for semiconductor behavior by solid state device theory [15]. Generally at high temperature, probability of finding electrons in the higher energy state is more. At sufficiently high temperature, almost all the electrons jump to energy states above Fermi energy. Electrons at such high energy state freely move as they are not tightly bound to nucleus. Now if the temperature is slowly reduced, electrons will return to lower energy state in such a way that total energy of the whole system is even lesser than it was before heating.

The model can be best described by solid state physics theory. Allowed electronic energy states in the conduction band can be termed as:

$$G_c(E) = \frac{4\,\pi(2m_n^*)3/2}{h^3}\sqrt{E - E_c}\ . \qquad (1)$$

Similarly allowed energy states in the valence band can be termed as:

$$G_v(E) = \frac{4\,\pi(2m_p^*)3/2}{h^3}\sqrt{E_v - E}. \qquad (2)$$

Probability of electrons at energy E is:

$$\frac{N(E)}{g(E)} = \frac{1}{1+\exp\left(\frac{E-E_f}{kT}\right)}\ . \qquad (3)$$

This can be approximated by:

$$\frac{N(E)}{g(E)} = exp^{-\left(\frac{E-E_f}{kT}\right)}. \qquad (4)$$

So number of electrons in conduction as below:

$$N_o = 2\left(\frac{2\pi m_n^* kT}{h^2}\right)^{3/2} exp^{-\left(\frac{Ec-E_f}{kT}\right)}. \qquad (5)$$

Number of electrons in valence band:

$$P_o = 2\left(\frac{2\pi m_p^* kT}{h^2}\right)^{3/2} exp^{-\left(\frac{Ef-E_v}{kT}\right)}\ . \qquad (6)$$

Equation (5) & (6) conform to the statement that if temperature is increased number of electrons at higher energy state will also increase. Consequently number of electrons at lower energy state will decrease. Again if temperature is reduced, number of electrons at lower energy state will increase. Thus if temperature is increased and then reduced sufficiently slowly, electrons will settle at lower energy states of valence band. Slow cooling will allow electrons at conduction band to slowly settle down at valence band without rushing. Thus overall stability of the system will increase even before heating. Energy can be compared to cost function of MPPT algorithm. It is the inverse of power output from the panel which is to be minimized. Duty cycle can be thought as analogous to electrons. At higher temperature, probability of finding duty cycle corresponding to garbage power output is more.

But if temperature reduces, probability of selecting duty cycle corresponding to higher power output increases. At sufficiently low temperature, probability of selecting duty cycle corresponding to maximum power is unity. Thus oscillation is damped totally at steady state operation. So, steady state error will be absolute zero without using closed loop control scheme. As open loop iterative control scheme is being employed, no stability problem will arise. Furthermore, this algorithm solves the problem of getting stuck in local, non-global minima, when searching for global minima. SA algorithm depends on continuous learning rate of the system at each iteration. Best result for suitable purpose can be obtained by proper selection of parameters such as temperature, tolerance error and temperature reduction factor.

Step 1: Generate random duty cycle, D_i
Step 2: Measure corresponding PV current, I_i and voltage, V_i
Step 3: Calculate input power, $P_i=V_i*I_i$
Step 4: Generate random duty cycle, D_k
Step 5: Measure corresponding PV current, I_k and voltage, V_k
Step 6: Calculate input power, $P_k=V_k*I_k$
Step 7: Cost function, ζ_i=offset-P_i
Step 8: Cost function, ζ_k=offset-P_k
Step 9: If $\zeta_k<\zeta_i$ then $D_i=D_k$
Step 10: Else if $\zeta_k>\zeta_i$ compute f=Exp $(\zeta_i-\zeta_k)/T$
Step 10.1: If f>tolerance, $D_i=D_k$
Step 10.2: Else if f<tolerance, $D_i=D_i$
Step 11: T=T-tolerance*T/sensitivity.
Step 12: Jump to step (4) for finite number of iterations.

Offset must be greater than desired maximum power (MP). Best result can be obtained if difference between offset and desired maximum power is greater than twice the MP and less than ten times MP. Sensitivity which determines temperature reduction factor should be low for rapidly changing weather pattern. A higher sensitivity and lower tolerance is suited for slow changing weather pattern where steady state error is more a decisive factor than quick settling time.

IV. Simulation Result for SA

Proposed algorithm is tested under three different weather conditions. At each successive simulation of the algorithm even at fixed temperature and irradiance pattern shows various curves because of different random variables. Settling time may differ but all the results show conformity with the fact than finally SA algorithm successfully tracks Maximum Power Point(MPP) with null steady state error. Fig: 4-6 shows the convergence to maximum power point for a typical light intensity of 1000W/m^2 at ambient temperature of 25^{0}C for an MSX 60 solar panel. The three figures are taken from three successive run of MATLAB code. Fig: 7-9 shows maximum power point tracking if light intensity drops to 500W/m^2 at ambient temperature of 25^{0}C. This weather pattern is changed drastically to testify the performance of the proposed algorithm for a rapid change in irradiance pattern. The three figures are taken from three successive run of MATLAB code. Fig: 10-12 shows maximum power point tracking if the temperature jumps to 50^{0}C at typical light intensity of 1000W/m^2. This weather pattern is changed drastically to testify the performance of the proposed algorithm for a rapid change in temperature profile. The three figures are taken from three successive run of MATLAB code.

A. Light intensity 1000W/m^2, T=25^{0}C

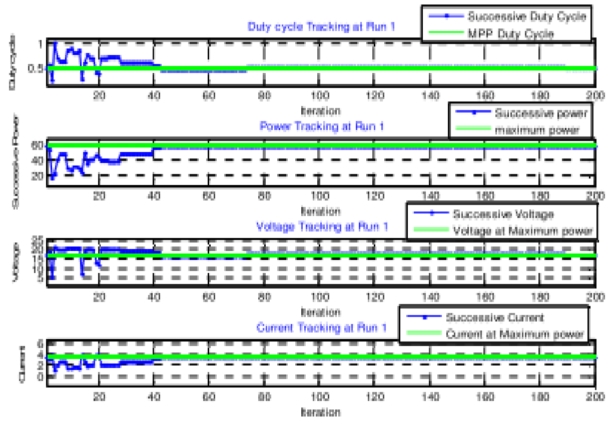

Fig. 4: Performance Tracking at run time 1

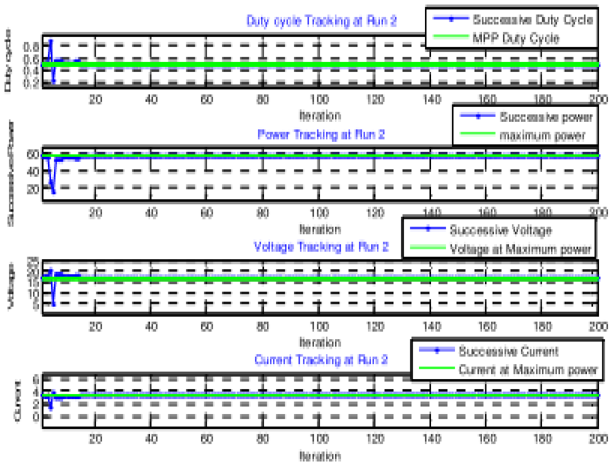

Fig. 5: Performance Tracking at run time 2

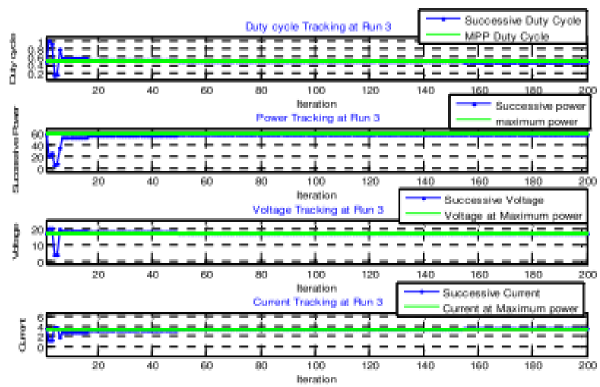

Fig. 6: Performance Tracking at run time 3

B. Rapidly changing weather conditions; Light intensity 500W/m^2, T=25^{0}C

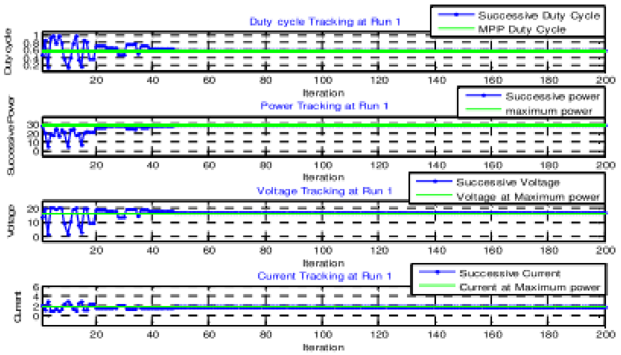

Fig. 7: Performance Tracking at run time 1

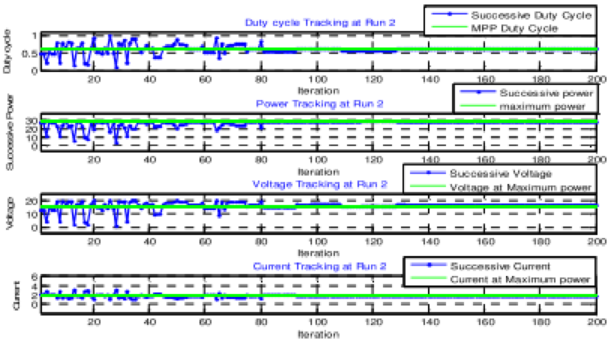

Fig. 8: Performance Tracking at run time 2

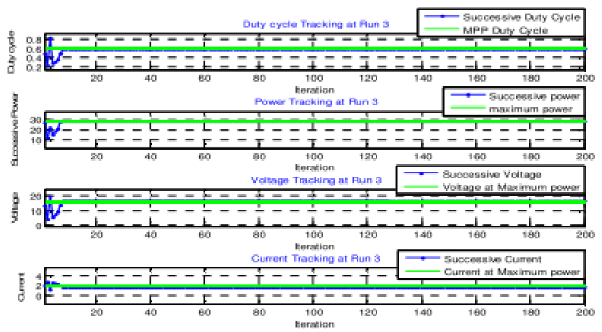

Fig. 9: Performance Tracking at run time 3

C. Rapidly changing weather conditions; Light intensity 1000W/m^2, T=50^{0}C

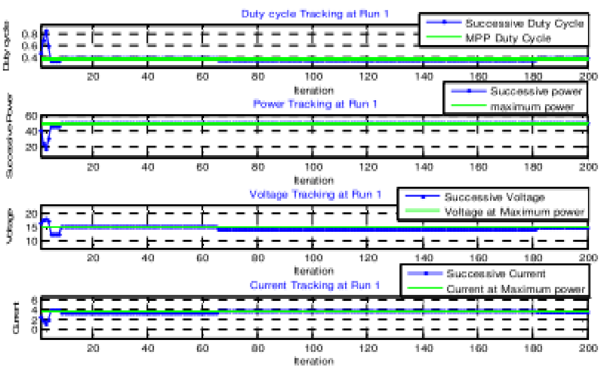

Fig. 10: Performance Tracking at run time 1

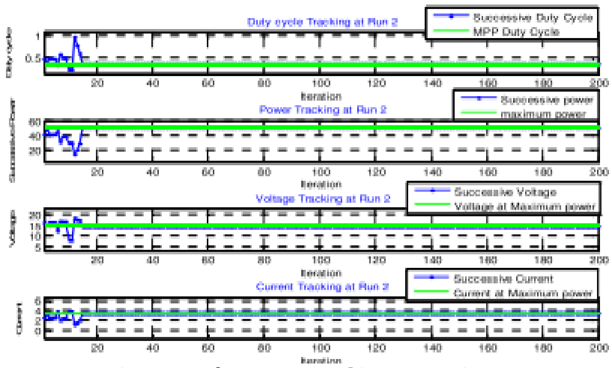

Fig. 11: Performance Tracking at run time 2

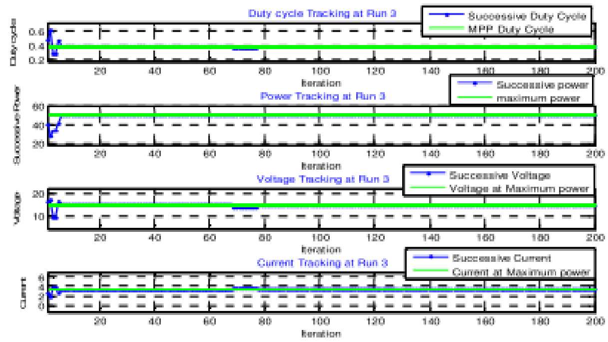

Fig. 12: Performance Tracking at run time 3

V. Algorithm for Fuzzy Logic(FL)

Fuzzy Logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. In contrast with "crisp logic", where binary sets have binary logic, the FL variables may have a membership value of not only 0 or 1 – that is, the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values of classic propositional logic. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. During the past decade, FL has been adopted to model complex systems [3]. FL is a mathematical system in which rigorous logical mathematics is used to deal with fuzzy information and data that are difficult to compute using conventional mathematics[4]. Fuzzy-logic-based modeling methodologies can be classified into two types [5]. The first type is used for developing purely linguistic models, based on conventional fuzzy implication and reasoning. The system behavior is described by means of fuzzy relational equations. A typical linguistic model is expressed as `IF x is A THEN y is B', where A and B are fuzzy sets. In this type of model, the fuzzy sets are determined subjectively, on the basis of experience. Quantitative information is seldom directly used for the determination of the model structure and parameters [6].There is an alternative type of modeling. This model, referred to as `the T-S model' in this text, consists of a number of fuzzy implications (FIs). Each FI is composed of a set of premises in the IF part and a set of consequences in the THEN part. The 'IF' part provides a logic based guidance to the use of regression models in the 'THEN' part. The T-S model structure has attracted much attention in recent years [8],[9]. FL algorithm has been successfully applied in various temperature tracking applications.

One of the major problems in proper utilization of FL in MPPT is that the maximum temperature to be tolerated remains confined within a known boundary in temperature detection application, but the MPP keeps sliding across the boundary depending on Irradiance and Temperature in MPPT application. To solve the problem, boundary of crisp value has been intelligently squeezed or expanded depending on latest previous values to obtain a higher precision of Fuzzy value. Again, in high power application, high precision is more a decisive factor than settling time. But in rapidly changing weather pattern, fast response time is desired. So precision and iteration limit should be changed accordingly to meet the desired performance for specific application. In FL algorithm by controlling step size and step number, convergence time and steady state error can be controlled effectively. Also the function used for fuzzying the crisp value can be a determining factor. Linear function is most simple and popular, but rectified sine function can also be used with some sacrifice of algorithm simplicity.

Step 1: Define sensitivity, step size and step number. Define function for fuzzying crisp value. In this paper linear function with a step number of nine is used.

Step 2: Generate random duty cycle (D2).
Step 3: Generate random duty cycle (D1).
Step 4: Measure corresponding current and voltage.
Step 5: Calculate power using measured value of voltage and current.
Step 6: Find Fuzzy value of current, voltage and power.
Step 7: P_low_low_fuzzy= min(I_high_high_fuzzyV_low_low_fuzzy)
P_high_low_fuzzy= min(I_high_high_fuzzyV_medium_low_fuzzy)
P_low_medium_fuzzy= max(min(I_high_high_fuzzyV_high_low_fuzzy)min(I_low_low_fuzzyV_high_high_fuzzy))
P_medium_medium_fuzzy= max(min(I_high_highfuzzy,V_low_medium_fuzzy)min(I_medium_low_fuzzyV_high_high_fuzzy))
P_high_medium_fuzzy= max(min(I_high_high_fuzzy,V_medium_medium_fuzzy)min(I_low_medium_fuzzy.V_high_high_fuzzy) min(I_high_low_fuzzyV_high_high_fuzzy))
P_low_high_fuzzy= max(min(I_high_high_fuzzyV_high_medium_fuzzy) min(I_medium_medium_fuzzy V_high_high_fuzzy))
P_medium_high_fuzzy= max(min(I_high_high_fuzzy,V_low_high_fuzzy)min(I_low_high_fuzzyV_high_high_fuzzy)min(I_high_medium_fuzzy V_high_high_fuzzy))
P_high_high_fuzzy= min(I_medium_high_fuzzyV_medium_medium_fuzzy)
Step 8: If P_high_high_fuzzy> resolution 1 and P_medium_high_fuzzy> resolution 2, Then D2=D1.
Step 9: Else jump to step 3.
Step 10: D2 contains desired duty cycle.

VI. Simulation Result for FL

Proposed algorithm of FL is tested under three different weather conditions. At each successive simulation of the algorithm even at fixed temperature and irradiance pattern shows various curves because of different random variables. Settling time may differ but all the results show conformity with the fact that finally FL algorithm successfully tracks MPP with reduced steady state error.

Fig. 13-22 shows the parameter tracking performances of our proposed FL algorithm under different weather conditions.

A. Light intensity 1000W/m^2, T=25^{0}C

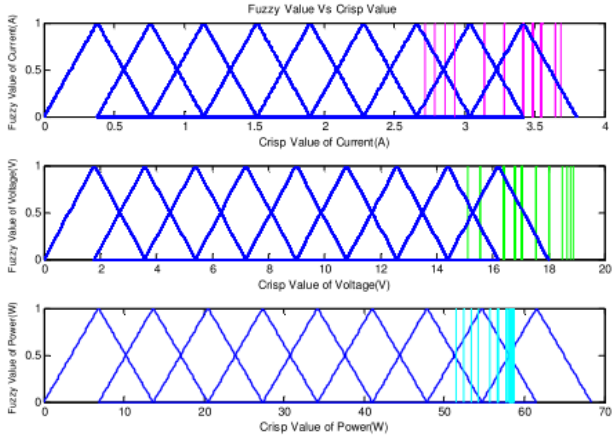

Fig. 13: Fuzzy value Vs Crisp value

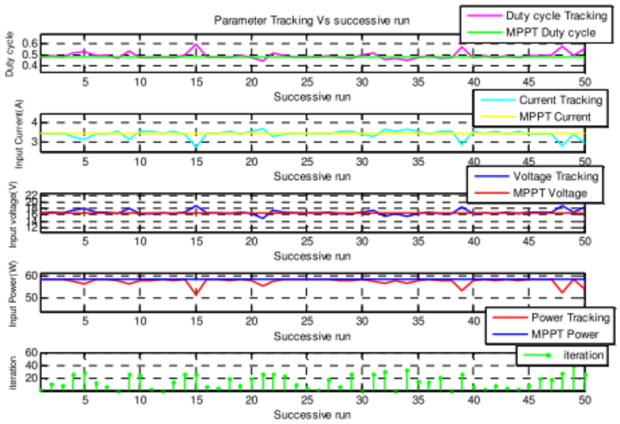

Fig. 14: Parameter tracking after defuzzying

Fig. 13 & 14 show performance of FL algorithm at standard light intensity of 1000 W/m2 and Temperature of 250C. Fig. 13 shows successive current, voltage and power tracking if the program is run 50 times. Being synthetically intelligent algorithm, each result chooses separate solution way to reach destination. Although current and voltage has a wide range of selectivity, power is densely clustered around MPP. Fig. 14 shows current, voltage, power duty cycle and number of iteration needed to within the region of acceptance at each successive run of total 50 run of the program.

B. Weather conditions changed rapidly to Light intensity 500W/m^2, T=25^{0}C

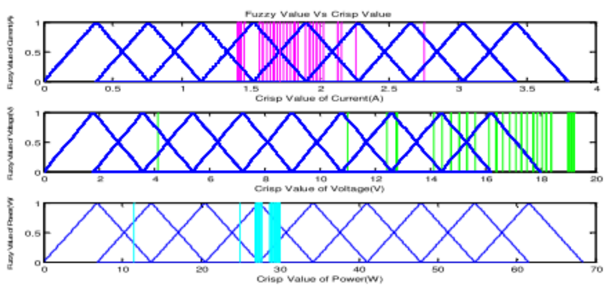

Fig 15: Fuzzy value and Crisp value at runtime 1

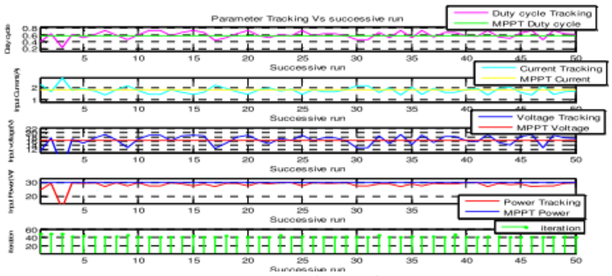

Fig 16: Parameter tracking after defuzzying at runtime 1

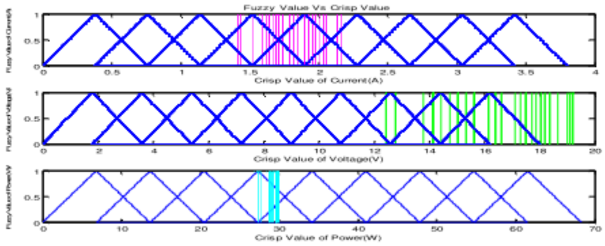

Fig 17: Fuzzy value and Crisp value at runtime 2

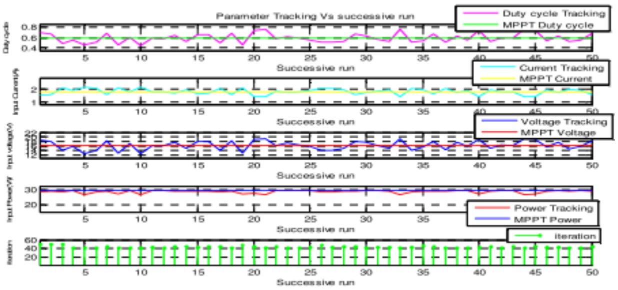

Fig 18: Parameter tracking after defuzzying at runtime 2

Fig. 15-18 shows performance if light intensity is halved to initial light intensity keeping Temperature same. It shows that power capability has been reduced by half of initial one. Initially it searches around maximum rated power of P-V panel. But from previous result, it trains itself to search around maximum power capability region at new weather condition. Above figures show that even though power has been changed, proposed algorithm successfully tracks power with negligible ripple around MPP point. Further precision can be obtained with some sacrifice of quick settling time.

C. Weather conditions changed rapidly to Light intensity 1000W/m^2, T=50^{0}C

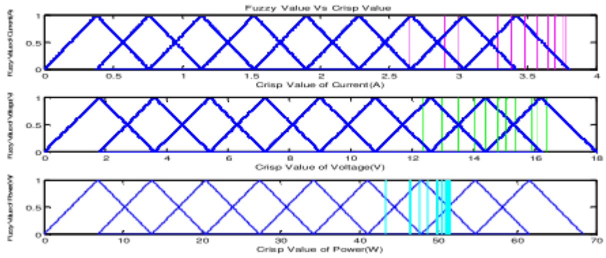

Fig 19: Fuzzy value and Crisp value at runtime 1

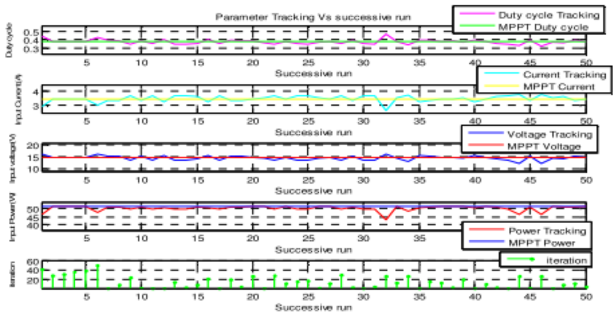

Fig 20: Parameter tracking after defuzzying at runtime 1

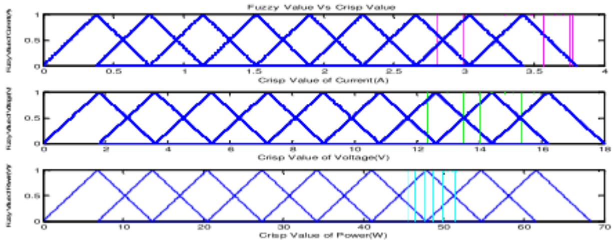

Fig 21: Fuzzy value and Crisp value at runtime 2

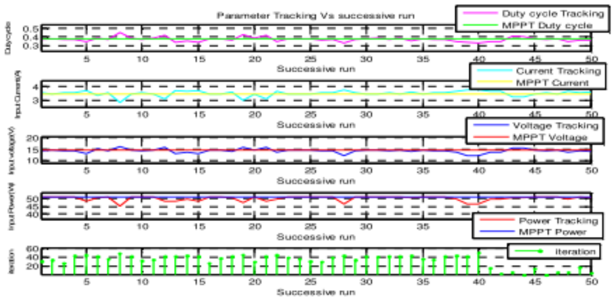

Fig 22: Parameter tracking after defuzzying at runtime 2

Fig. 19-22 shows performance of proposed algorithm at light intensity of 1000 W/m2 and Temperature of 50 C. Power capability is slightly less than previous one and open circuit voltage has reduced this time. Yet FL algorithm is reliable and quick to track desired duty cycle, hence power, voltage and current with settling time less than one milli-second. To test reliability of algorithm, in each of figures shown above, algorithm is tested 50 times. So each of the fifty points in the graph shows tracked power after successive number of iterations of fifty times.

VII. Algorithm for PSO

PSO algorithm is very simple yet it offers a great deal of flexibility to suit changing weather conditions by adjusting few parameters. Here two parameters defined as own learning rate and learning rate from neighbors are updated at each iteration. As the iteration number increases own learning rate increases and neighbors' influence decreases making the swarms intelligent by themselves.

Step 1: Initialize own learning rate, L_o=0. Initialize learning rate from neighbors, L_n=1 Initialize number of iterations, Ite=15
Step 2: Generate 4 random duty cycles $[SWRM]_i$
Step 3: Calculate $[P]_i$ corresponding to $[SWRM]_i$
Step 4: Duty cycle corresponding to Pmax is considered global variable.

Step 5: $[SWRM]_i+1=L_o*[SWRM]_i +L_n*[global]-[SWRM]_i$ – $L_n*_i*[global]-[SWRM]_i/Ite$.
Step 6: i=i+1, Ln = Ln- sensitivity, $L_o=L_o+$ sensitivity
Step 7: Jump to step 3 until i=Ite
Step 8: [SWRM] contains the desired duty cycle tracked by 4 intelligent swarms.
Step 9: [P] Corresponding to [SWRM] is the desired MPP.

VIII. Simulation Result for PSO

Proposed algorithm of PSO is tested under three different weather conditions. At each successive simulation of the algorithm even at fixed temperature and irradiance pattern shows various curves because of different random variables. Settling time may differ but all the results show conformity with the fact than finally PSO algorithm successfully tracks MPP with reduced steady state error. Fig: 23-26 shows the convergence to maximum power point for a typical light intensity of 1000W/m2 at ambient temperature of 250C for an MSX-60 solar panel for four intelligent swarms. Fig.27-30 shows maximum power point tracking if light intensity drops to 500W/m2 at ambient temperature of 250C. This weather pattern is changed drastically to testify the performance of the proposed algorithm for a rapid change in irradiance pattern. Fig: 31-34 shows maximum power point tracking if the temperature jumps to 500C at typical light intensity of 1000W/m2. This weather pattern is changed drastically to testify the performance of the proposed algorithm for a rapid change in temperature profile.

A. Light intensity 1000W/m^2, T=25^{0}C

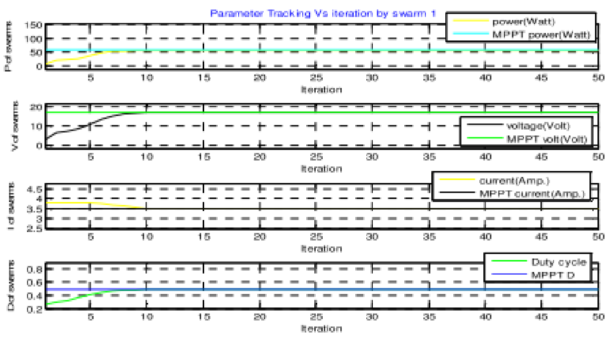

Fig 23: Parameter tracking by swarm 1

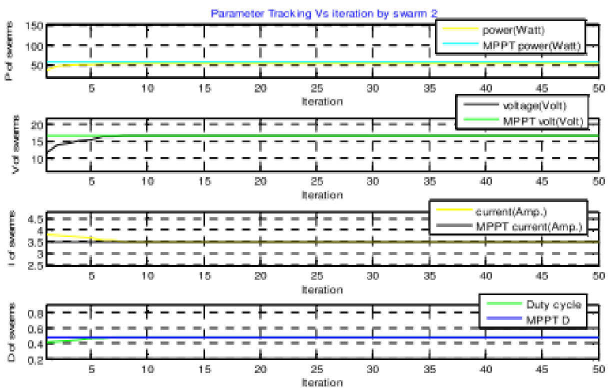

Fig 24: Parameter tracking by swarm 2

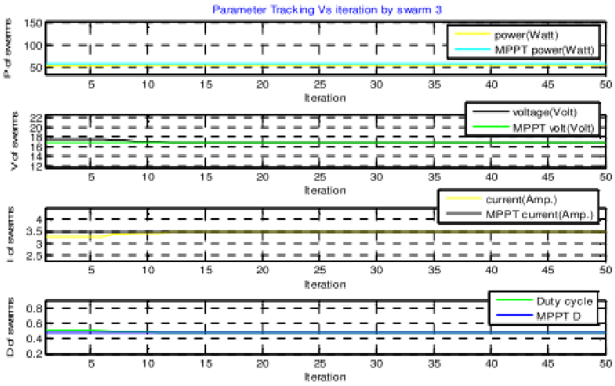

Fig 25: Parameter tracking by swarm 3

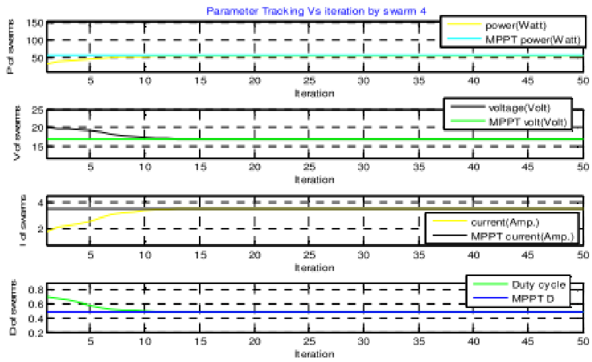

Fig 26: Parameter tracking by swarm 4

Fig. 23-26 Shows that four swarms converge to maximum power point though their initial position (Duty cycle) was different. Based on neighbor's decision and own experience, the swarms continuously change their travelling direction (Duty cycle) so that they can reach destination with minimum travelling distance (Iteration). Fig. 27-30 shows that PSO algorithm tracks maximum power point even though the intensity has been decreased to half of initial intensity. Four figure shows convergence of four swarms to destination (MPP).Swarms can successfully reach desired destination point even though the destination has been changed.

B. Weather conditions changed rapidly to Light intensity 500W/m^2, T=25^{0}C.

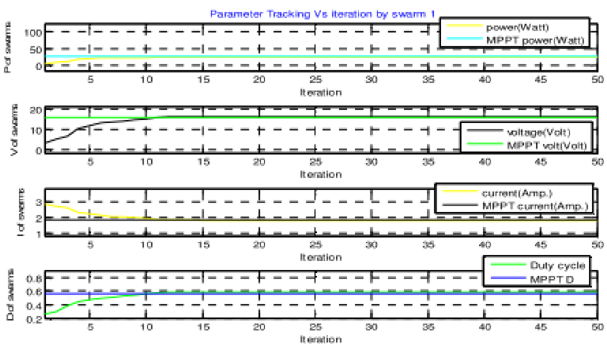

Fig 27: Parameter tracking by swarm 1

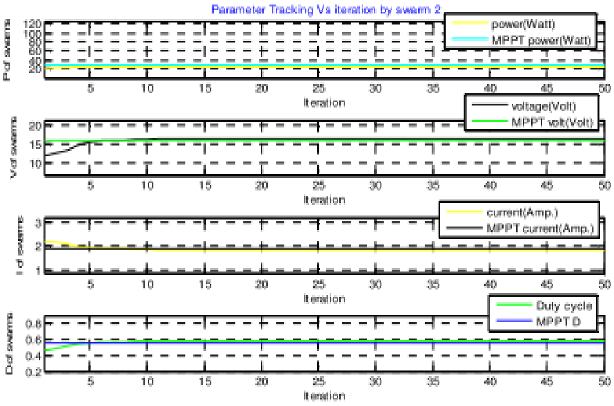

Fig 28: Parameter tracking by swarm 2

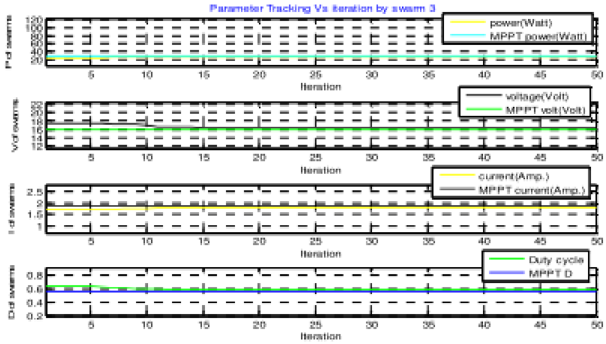

Fig 29: Parameter tracking by swarm 3

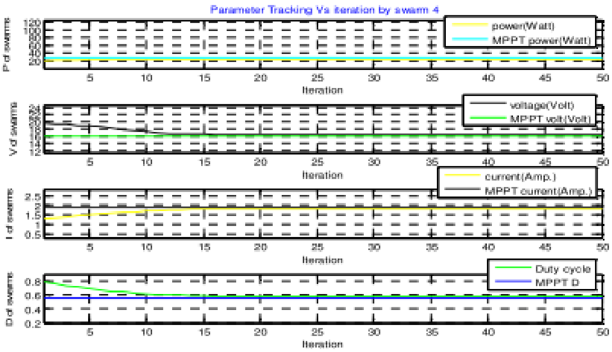

Fig 30: Parameter tracking by swarm 4

C. Weather conditions changed rapidly to Light intensity 1000W/m^2, T=50^0C.

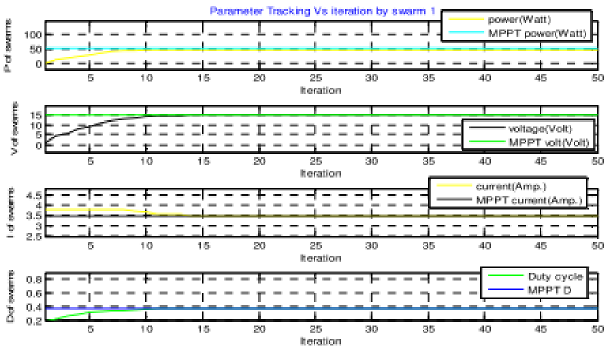

Fig 31: Parameter tracking by swarm 1

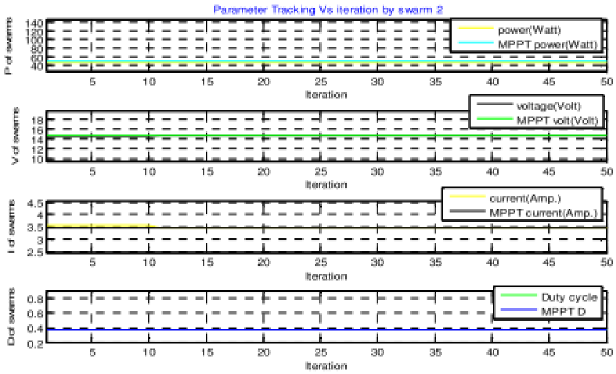

Fig 32: Parameter tracking by swarm 2

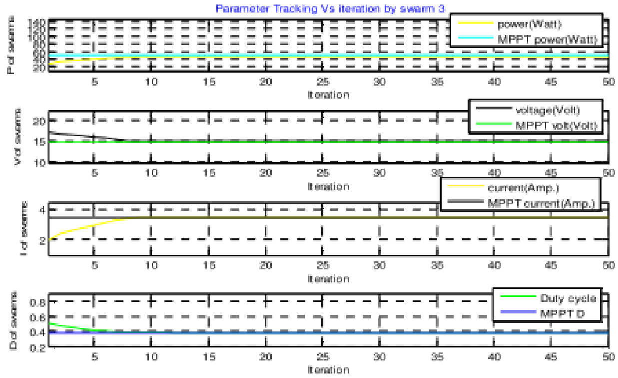

Fig 33: Parameter tracking by swarm 3

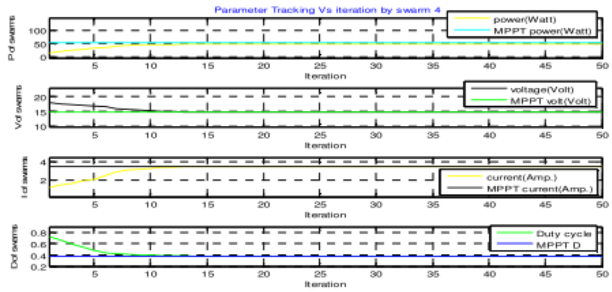

Fig 34: Parameter tracking by swarm 4

Fig. 31-34 shows PSO algorithm can track MPP even if temperature changes drastically. Four figures shows solution curve for four intelligent swarms.

IX. Practical Circuit Structure

Microcontrollers are more flexible than analog circuitry. Traditional PO has become popular because of its easy implementation with comparator, multiplier and operation amplifier. But now-a-days even complex mathematical computation can be performed at ease with a single microcontroller cheaply only by efficient programming. Moreover, microcontrollers are far better than FPGA because of low cost and hardware simplicity.

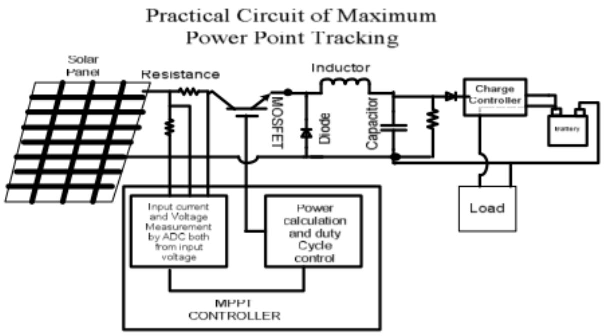

Fig 35: Practical Circuit implementation with MPPT

In Fig. 35, MPPT controller determines the maximum power that can be extracted from solar panel. Then depending on MPP duty cycle, it controls the pulsing signal to the buck converter that feeds the battery. Buck converter actually behaves like a DC transformer. Duty cycle determines the virtual impedance of the converter circuit that PV panel faces across its terminals. A charge controller is usually connected to prevent battery overcharging back flow of power to PV panel. Load is also connected to battery through charge controller to prevent battery under charging.

X. Algorithm for GA

Step 1: Initialize EEPROM of microcontroller with duty cycle from .1 to .9 randomly in a resolution of .005 in the first 320 bytes of ATMEGA8. Duty cycle is multiplied by 1000 and converter integer values are stored as High byte and Low byte.
Step 2: Initialize EEPROM of microcontroller with numbers 1 to 160 randomly in the second 512 bytes of ATMEGA8.
Step 3: Increment a number from 1 to 160 sequentially and read corresponding EEPROM value from the second portion of EEPROM. Save it as index.
Step 4: According to index, chose corresponding value from first portion of EEPROM. It will be treated as random duty cycle.
Step 5: Any of the PORTS is initialized as output port. According to selected duty cycle, On-Off period of a pin is controlled correspondingly. The function can be performed more accurately using Compare and Match function of Timer 2 using PWM/Fast PWM technique.
Step 6: If voltage driven switch like MOSFET/IGBT is used in the buck circuit no extra IC is required. If current driven switch like SCR/BJT is used a buffer IC like ULN2003 will be required between microcontroller pin and control pin of switch.
Step7: Voltage is measured through a High Known Resistance across terminal of solar panel using Built-in ADC of 10 bits.
Step 8: Current is measured by dividing voltage across small line resistance by known resistance.
Step 9: Then proposed algorithm (SA/FL/PSO) is incorporated with the microcontroller.

XI. Performance Comparison

Particle swarm optimization (PSO), Fuzzy Logic(FL) controller, Genetic algorithm (GA) is most popular synthetically intelligent algorithms [13],[14]. The simulation has been performed with the same PV panel under same weather profile using all three algorithms. Fig 23-34 shows performance of PSO algorithm. It shows that PSO algorithm is fast and robust and it is reliable even under rapidly changing weather pattern, but it has steady state error.

Fig 13-22 shows performance of FL controller. It shows that FL is most reliable but it has a slow response and non-zero steady state error. However, results show that though voltage and current of PV panel is changed over a wide range, Power is highly concentrated around MPP. This is why; it offers a great flexibility in designing Buck converter. Fig 36-38 shows Genetic algorithm performance at the same test conditions that are applied to SA, PSO and FL performance. Results are obtained from the fittest gene that survived after finite number of Cross-over and Mutation.

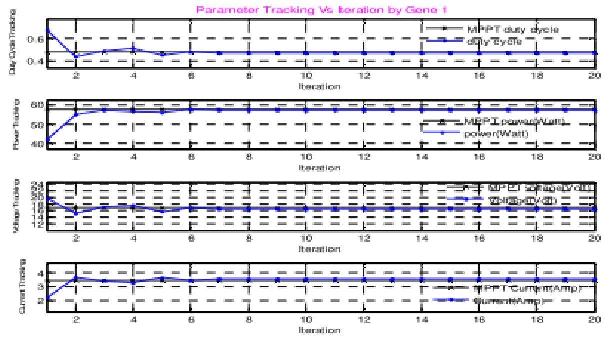

Fig 36: GA performance at T=25^{0}C, I=1000W/m2

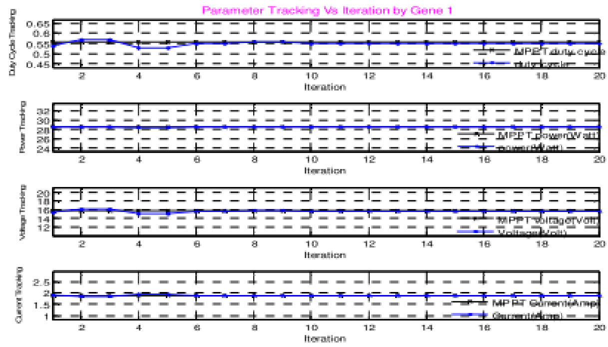

Fig 37: GA performance at T=25^{0}C, I=500W/m^2

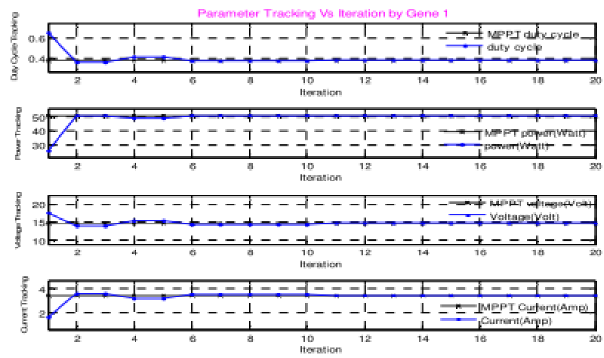

Fig 38: GA performance at T=50^{0}C, I=1000W/m^2

Comparing different parameters, it is evident that each algorithm is suited for different purposes. SA algorithm is most suited for high power PV array because of its negligible steady state error. PSO is most suited for fast and rapidly changing weather while FL is most suited where designing Buck converter needs a greater range of parameter flexibility. In cascaded network where loading effect can change the Buck converter performance, FL is most suitable. Below table shows a comparison between these algorithms.

Algorithm	Settling Time	Steady State Error	Reliability
PSO	Low	Medium	High
FL	High	Medium	High
SA	Medium	Null	Medium
GA	Low	High	Medium

Fig. 39 & 40 summarizes the performance described in the Table. I. It shows the relative comparison of steady state error (%) and settling time between all the algorithms discussed above at all the test conditions.

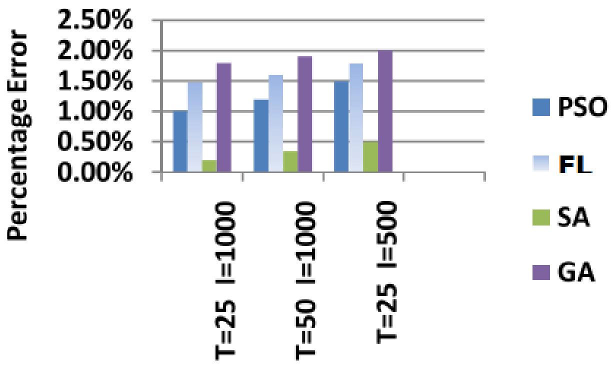

Fig 39: Percentage errors at test conditions

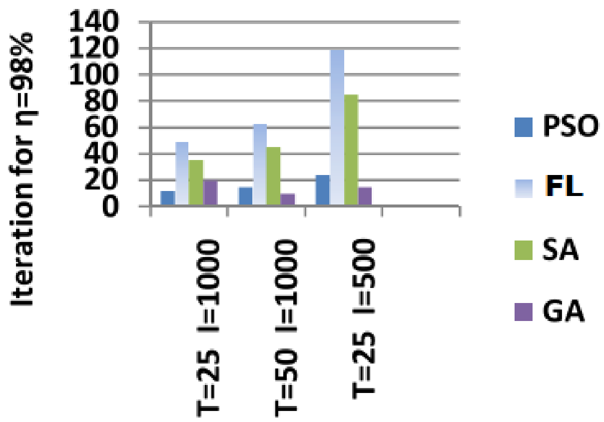

Fig 40: Iteration Number for 98% convergence at Test Conditions

XII. Conclusion

Few algorithms such as FL, PSO, SA have been developed in this paper and a comparative study has been performed to sort out the best one considering settling time, steady-state error, reliability. Further investigation might be carried out to improve the efficiency, response time, parameter optimization etc.

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Authors' Biography

[1]**Md. Hasibur Rahman** accomplished B. Sc. in Electrical and Electronic Engineering (EEE) from Bangladesh University of Engineering and Technology (BUET) in 2008. Currently Mr. Rahman is working in Baglalink Digital Communication Ltd.

[2]**Swadesh Poddar** finished B. Sc. in Electronics & Communication Engineering (ECE) from Khulna University, Bangladesh in 2011.

[3]**Mohammad Mahbubur Rahman Khan Mamun** successfully completed B. Sc. in Electrical and Electronic Engineering (EEE) from Bangladesh University of Engineering and Technology (BUET) in 2009. Now he is working in Baglalink Digital Communication Ltd.

[4]**Selim Mahmud** achieved B. Sc. in Computer Science and Engineering (CSE) from Bangladesh University of Engineering and Technology (BUET) in 2008. Presently he is working in Robi Axiata Ltd.

[5]**Md. Tanvir Yeasin** received B. Sc. in Electrical and Electronic Engineering (EEE) from Ahsanullah University of Science and Technology (AUST) in 2007.