Seasonal-Adaptive Integral Sliding Mode Controller Based MPPT: A Case Study of Addis Ababa Area

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***Abstract*—Solar PV systems are one of the scalable and environmentally beneficial energy resources. MPPTs are used to maximize energy harvest from the solar PV. The change in environmental conditions degrades the efficiency of MPPT algorithms. The classical MPPTs are poor in performance under variable environmental conditions. Therefore, an adaptive and robust MPPT controller is required to harvest maximum energy from the solar panel. The real site measured data of irradiance and temperature from the Addis Ababa Bole area are collected. The collected data show frequent irradiance changes and strong seasonal variation. Seven MPPT controllers are simulated and compared using MATLAB under sudden irradiance change and by adding stochastic noise to the collected data. The industry standard P&O and INC are poorly performing under the sudden irradiance change and stochastic noise. The classical SMC possesses chattering unless their high performance. The proposed seasonal adaptive(SA)-ISMC outperforms all MPPT algorithms with the highest efficiency(99.81%), minimum IAE(0.13), and ISE(2.60). SA-ISMC continuously adapts to changes in the environment and is robust with minimum ISE. The rainy season is characterized by low energy yield, which is the complement of hydro-power generation in Ethiopia and a promising solution in both micro-grid and grid-connected systems.**

***Index Terms*—Adaptive Controller, MPPT, SA-ISMC, Tracking efficiency, PV system**

I. Introduction

Solar power is clean, silent, and long lasting due to high sun light availability and uniform in Ethiopia and there is a need for renewable energy in the region and the world. PV energy production depends on several factors, including insolation, system size (kW), and system efficiency. The efficiency of the system can be affected by various factors, such as dust or soil accumulation on the panel, wiring mismatches, and inverter inefficiencies [1].

Ethiopia possesses exceptional solar energy potential, a key resource for diversifying its hydro power dependent grid and expanding energy access which receives high levels of daily solar irradiation averaging over $5.5kWh/m^2$ [2]. The region's moderate temperatures makes favorable for optimal photovoltaic (PV) panel performance. The maximum power point tracking(MPPT) are used to maximize the maximum energy from the available solar resources to boost PV system efficiency, battery longevity, improved reliability, safety, and scalability. But, There is always a challenge to get the precise maximum power point(MPP) due to nonlinear I-V characteristics of PV sources and rapidly changing atmospheric conditions mainly the temperature and irradiance. The algorithm continuously scans for the optimal operating point to ensure maximum efficiency. However, in cases of sudden environmental changes, the tracker often remains at a local Maximum Power Point (MPP), which may not be the global MPP [3].

II. Related Works

The main MPPT categories are conventional, meta-heuristics, and artificial intelligence(AI) shown in Fig. 1. Various MPPT methods have emerged in the last decades,

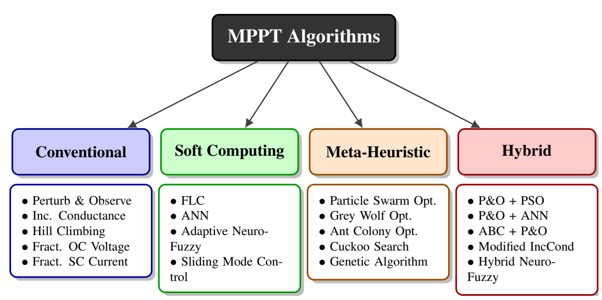

Fig. 1: Classification of MPPT approaches [4]

such as, Perturb and observe (P&O) [5], Incremental conductance [6], Hill-climbing (HC) [7], Fractional open-circuit voltage (FOV) [8], Fractional short-circuit current (FSC) [9], Genetic Algorithm(GA) [10], Particle swarm Optimizer(PSO), Gray Wolf Optimizer(GWO) [11], Anti-colony optimizer(ACO) [12], Sliding Mode Controller(SMC), Fuzzy Logic Controller(FLC), Artificial Neural Network(ANN) and more.

Conventional MPPT algorithms react to changes in power, which introduces delays and oscillations, leading to energy loss. P & O MPPT algorithm is easy to use and simple for implementation but there is a concern for rapidly changing irradiance, high oscillation, and poor tracking speed. Also, in P & O there is a drawback in selection of perturbation size and if the current MPP is changed due to environmental changes, the P & O algorithm is unable to reach the MPP. Incremental conductance MPPT algorithm is developed to address the drawbacks of P & O but there is still imbalance and measurement mistakes due to its operation is derivative and high computational time. Soft Computing MPPT algorithms are Heuristic methods (GA, PSO, etc.) handle uncertainty well and moderate accuracy and complexity. Machine Learning based MPPT algorithms are Data-driven (ANN, SVM, RL, etc.), are highly adaptive and accurate, but they need data and have high computation. Furthermore, intelligent approaches like Fuzzy logic control (FLC), ANN, and GA have been also employed to track the MPP. However, there is gap in using the real-time data integration with robust controllers.

The Incremental Conductance algorithm works by differentiating power, $P = VI$ with $\frac{d}{dV}$ as shown in (1).

$$\frac{dP}{dV} \approx I + V\,\frac{\Delta I}{\Delta V} \tag{1}$$

At $\frac{dP}{dV} = 0$, the maximum power is reached.

PSO algorithms are meta-heuristic based algorithms in which the proposed swarm tracks for the highest power in multiple iterations [13]. However, they need high computational complexity and are parameter sensitive [14]. Also, they rely on multiple multiple iterations and when there is sudden irradiation change, temperature change, and load change the swarm may not track the MPP instantly [15].

In this paper the velocity update equation for the PSO based MPPT is given by (2) where c_1, c_2 are acceleration coefficients, r_1, r_2 are stochastic weights, and w is inertial weight.

$$V_{k+1} = wV_i(k) + c_1 r_1\left(pBest_i - x_i(k)\right) + c_2 r_2\left(pBest - x_i(k)\right) \tag{2}$$

The ANN reads the irradiance and temperature data in nanoseconds without hill-climbing and calculates the maximum power point voltage. In this paper, Bayesian($trainbr$) ANN is used. The hidden layer network of the forward path is given by

$$h_j = \tanh \sum_{i=1}^{2} \left(w_{jk} X_k + b_j\right) \tag{3}$$

III. Data Description and Site Characterization

The data are collected from Ethiopian Meteorology institute site and SP-Lite Pyranometer is used with 15-minute interval of a four year data. The annual energy yield(E_y) is given (4)

$$E_y = \left(\int_{\text{sun-rise}}^{\text{sun-set}} G(t)\,dt\right) \times 365\ \text{days} \tag{4}$$

The inter-annual energy yield variation is minimal($\leq$ 2%) but the energy yield in the three seasons is significantly fluctuating($>$ 10%). According to the data collected from Addis Ababa area shown in Fig. 3, the rainy

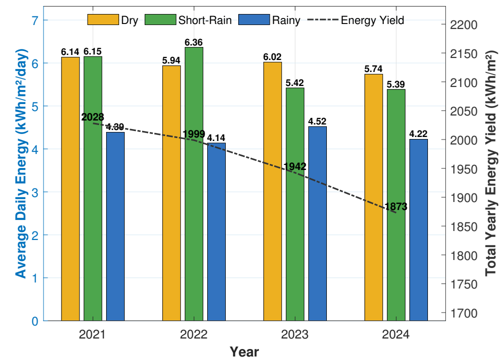

Fig. 2: Average Seasonal Energy Yield

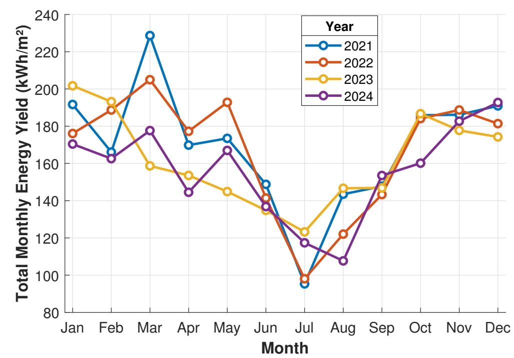

Fig. 3: Monthly Energy Yield Comparison (2021-2024)

season is characterized by low energy yield which is the complement of hydro-power generation in Ethiopia which covers approximately 90% of energy production in Ethiopia [16]. Therefore, the solar energy generates higher energy in the dry season while the hydro-power is generating low energy at the dry season. This leads to sufficient energy access to the country under seasonal changes.

The irradiance ramp rate of Bole area is $+62.76W/m^2/min$ maximum single irradiance increase and $-61.39W/m^2/min$ maximum single irradiance decrease in a minute interval and the stress day from the four year data is used for the MPPT algorithms. The irradiance ramp rate is given by (5):

$$RR(t) = \frac{|G(t) - G(t - \Delta t)|}{\Delta t} \tag{5}$$

Generally from the data analysis the study area is characterized by frequent irradiance fluctuation, strong seasonal variability, and dominated with medium irradiance level. Therefore, for a long-term energy extraction and yield a robust and adaptive MPPT algorithm is required.

IV. PV System Modeling

The significant effects on the output of power from PV system are solar irradiance and temperature [17]. There is a high correlation between PV power and environmental conditions. The simplified PV cell mathematical model is shown in (6) [18].

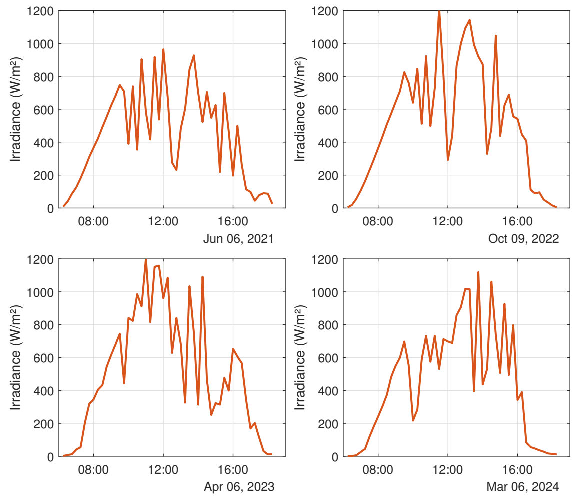

Fig. 4: MPPT Stress Test Days (Irradiance Profile)

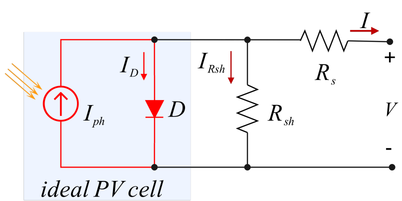

Fig. 5: PV cell equivalent model [19]

$$I = I_{ph} - I_0 \left[exp \left(\frac{q(V + IR_s)}{nKNT} \right) - 1 \right] - \left(\frac{V + IR_s}{R_{sh}} \right) \quad (6)$$

$$I_{ph} = [I_{SC} + K_i(T - 298)] \frac{G}{1000} \quad (7)$$

$$I_0 = I_{rs} \left[\frac{T}{T_n} \right]^3 exp \left[\frac{qE_{go} \left(1/T_n - 1/T\right)}{nK} \right] \quad (8)$$

$$I_{rs} = \frac{I_{SC}}{exp\left(\frac{qV_{oc}}{nN_s KT}\right) - 1} \quad (9)$$

where, I_0 is reverse saturation current and α is diode ideal factor. The DC-DC boost converter duty cycle D changes every sample from the collected data:

$$D(t) = 1 - \frac{V_{\text{MPP}}(t)}{V_L} \quad (10)$$

The Solar panel specification used in this paper are Peak power=305.00 W, Rated voltage(V_{mp}) = 54.70 V, Rated current(I_{mp}) = 5.58 A, Open Circuit Voltage(V_{oc})= 64.20 V, Short Circuit Current(I_{sc})=5.96 A, and Load voltage of 80 V. The DC-DC boost converter parameters design for the solar panel specifications and taking 30% of ripple for the power electronic parameters are $L = 250\mu H$, $C_{in} = 68\mu F$, $f_s = 50kHz$, and $R_L = 17.9\Omega$.

V. PROPOSED MPPT ALGORITHM

Sliding mode controller are robust controllers and have simple structure and good for real time hardware [20]. But, the high frequency change [21, 22] and sensitivity to measurement noise due to $\frac{dP}{dV}$ are the main drawbacks. Therefore, the SMC can track only the local MPP under random irradiance changes. The sliding surface for the SMC is given by (11) and

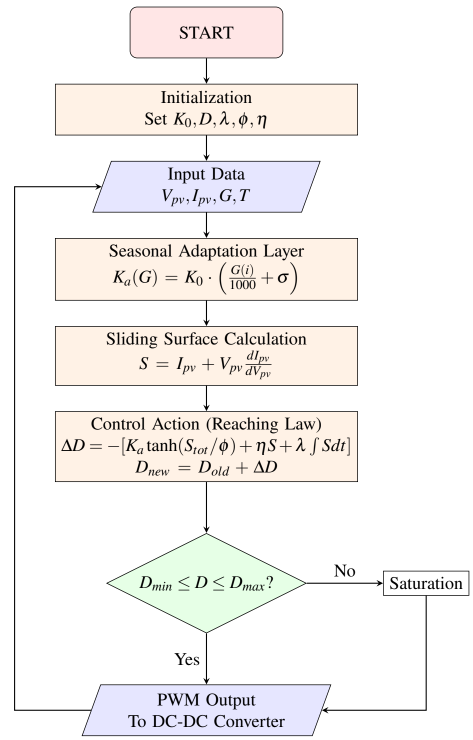

Fig. 6: Flowchart of SA-ISMC

the Quasi-sliding mode reaching law is given in (12) where K is the switching gain [21, 22] and ϕ is as a boundary layer.

$$S = I + V\frac{dI}{dV} \approx \frac{dP}{dV} \quad (11)$$

$$\Delta D_{\text{SMC}} = -K \tanh(S/\phi) \quad (12)$$

In the integral sliding mode controller(ISMC) [23] the reaching law is given in (13).

$$\Delta D_{\text{ISMC}} = -\left[K_1 \tanh(S/\phi) + K_2 S + \lambda \int S \, dt \right] \quad (13)$$

In the seasonal adaptive integral sliding mode controller(SA-ISMC) the reaching law is given in (14) and switching gains are adaptive. SA-ISMC solves this random irradiance changes as a function of the actual environmental data, where the seasonal adaptive law is given in (15) which makes adjustment for the controller(Fig. 7). In classical MPPT algorithms the change in voltage causes for the change in power but in SA-ISMAC the change in power is caused due to the change in irradiance ΔG where δ is small decimal value.

$$\Delta D_{\text{SA-ISMC}} = -\left[K_a(G) \tanh(S/\phi) + \eta S + \lambda(G,T) \int S \, dt \right] \quad (14)$$

$$\text{where,}\quad K_a = \left(\frac{G_{\text{actual}}}{G_{\text{STC}}} + \delta\right) \tag{15}$$

The stability of the SA-ISMC is proved using Lyapunov

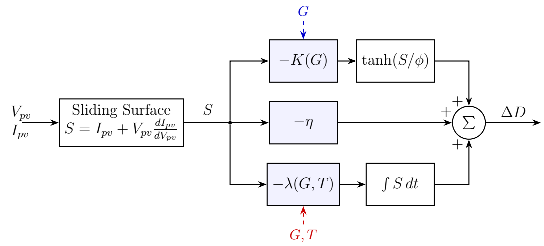

Fig. 7: SA-ISMC block diagram

positive definite function $V = \frac{1}{2}\sigma^2$ where $V(\sigma) > 0$ and $v(0) = 0$.

$$\dot{\sigma} = \dot{S} + \lambda S \tag{16}$$

$$\dot{S} = \frac{\partial S}{\partial V}\dot{V}_{pv} + \underbrace{\left(\frac{\partial S}{\partial G}\dot{G} + \frac{\partial S}{\partial T}\dot{T}\right)}_{D(t)} \tag{17}$$

where $D(t)$ is the environmental disturbance and from (14) and from the dynamics of DC-DC converter $\dot{V}_{PV} = -V_{load}\dot{D}$ and solving for $\dot{V}$:

$$\dot{\sigma} = -K_a|\sigma| - \eta\sigma + \sigma D(t) \tag{18}$$

Using $|\sigma D(t)| \leq |\sigma|\,|D(t)|$, then

$$\dot{V} = -|\sigma|\,(K_a - D(t)) - \eta\sigma^2 \tag{19}$$

$\dot{V} < 0$ must hold for the stable system and (20) is also hold.

$$K_a > |D(t)| \tag{20}$$

Then $\dot{V} < 0, \forall\sigma \neq 0$

VI. RESULT AND DISCUSSION

For the four year data the stress day is selected(Fig. 4) the irradiance data is highly volatile. For the performance analysis tracking efficiency(η), ISE/IAE, and robustness, Both transient robustness test (worst case irradiance change from $300W/m^2$ to $900W/m^2$) and stochastic stability test are considered for a 1000 ms duration. The transient robustness test is given by $G_{\text{step}}(t) = 300 + 600\,u(t - 0.5)$ where, $u(t - 0.15) = \begin{cases} 0, & t \leq 0.5 \\ 1, & t \geq 0.5 \end{cases}$ and the gaussian distribution is given by $G_{\text{Noise}}(t) = N\left(\mu, \sigma^2\right)$

The error is expressed as the difference in ideal and actual power delivered by the MPPT controllers.

$$IAE = \int_0^T |e(t)|dt = \sum_{i=1}^{N} |P_{\text{ideal,i}} - P_{\text{actual,i}}|\Delta t$$

$$ISE = \int_0^T e(t)^2 dt = \sum_{i=1}^{N} \left(P_{\text{ideal,i}} - P_{\text{actual,i}}\right)^2 \Delta t$$

For the comparison of all MPPTs the same parameter are

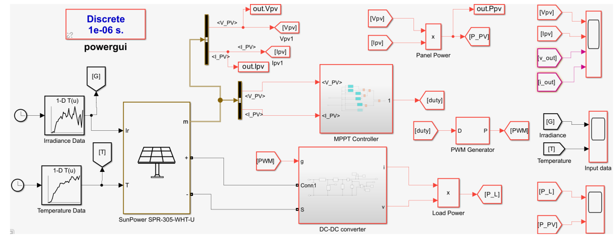

Fig. 8: Overall simulink diagram of the proposed system

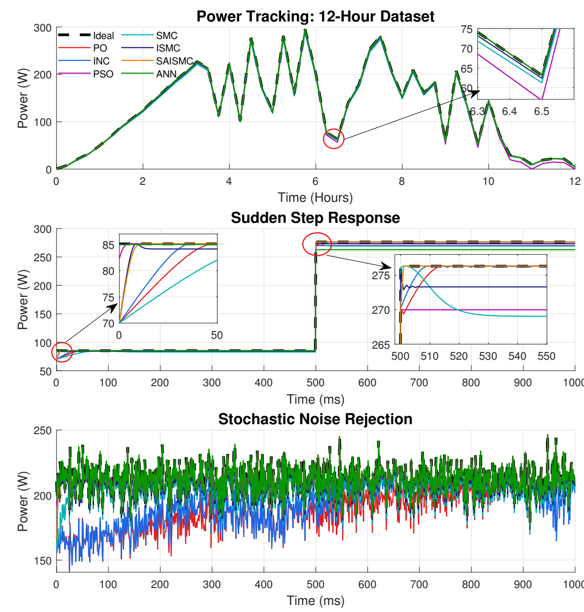

Fig. 9: Simulation result of P&O, INC, PSO, SMC, ISMC, ANN, and SA-ISMC MPPT algorithms

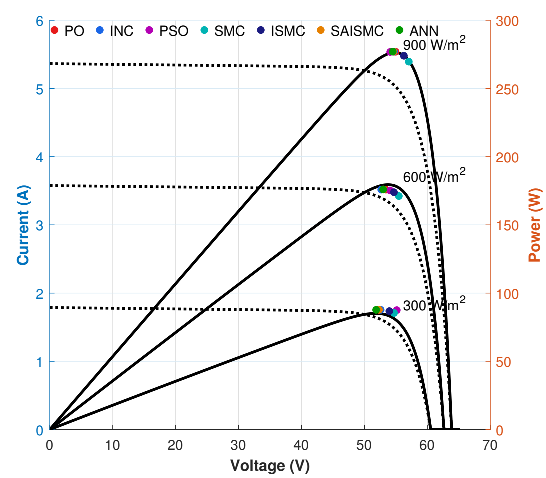

Fig. 10: P-V and I-V curve of P&O, INC, PSO, SMC, ISMC, ANN, and SA-ISMC MPPT algorithms

used. As shown from Fig. 9 both P&O and INC MPPTs are characterized by low tracking speed, poor noise rejection, and are not robust with low precision. The PSO is characterized by moderate tracking speed and robustness with high noise rejection capacity. The classical SMC is fast, robust and precise while there is a chattering. ANN instantly tracked the reference with moderate precision, however the SA-ISMC is very fast, more robust, maximum precision, and superior noise rejection as compared with the other MPPTs.
From Fig. 11 the SMC surface is sluggish which requires

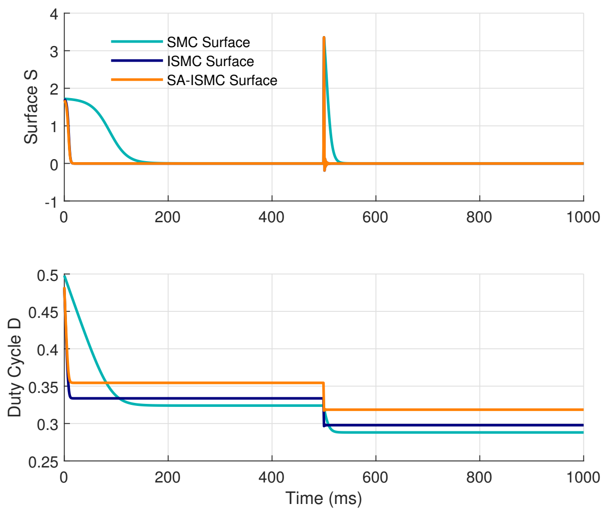

Fig. 11: Surface and duty cycle under step response test

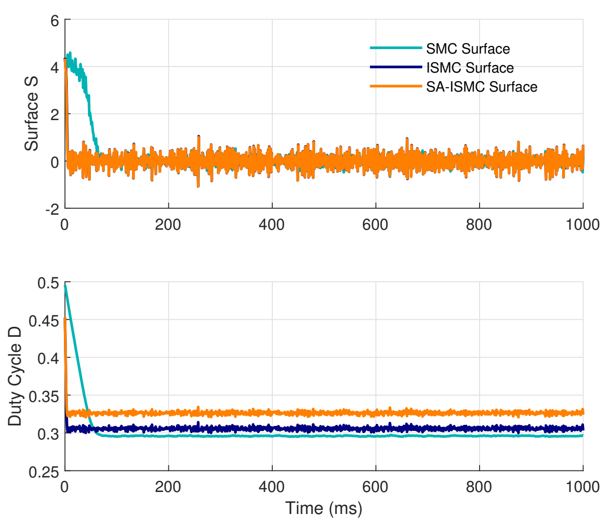

Fig. 12: Surface and duty cycle under stochastic noise test

nearly 150ms to force to zero error while the SA-ISMC almost instantaneously converges. As shown from Table I under sudden irradiance change and when the stochastic noise is added the performance of each MPPT algorithms are different. The industry standard P&O MPPT algorithm and the INC MPPT algorithms are performing poor performance due to their fixed step-size under stochastic noise in terms of efficiency(87.17%, 89.37%), IAE(27.22, 22.56), and ISE(858.93,658.57) respectively. The ANN performed high efficiency in the noise rejection but showed high ISE(147.77) in the sudden irradiance change. The SA-ISMC outperforms all MPPT algorithms in efficiency(99.81%), IAE(0.13), and ISE(2.60) which is aware of the irradiance changes and continuously adapts the change in parameter in both sudden irradiance change and stochastic noise.

TABLE I: Performance summary of the MPPT algorithms

		Sudden Step Response			Stochastic Noise Rejection		
MPPT	Data(%)	η(%)	IAE	ISE	η(%)	IAE	ISE
PO	99.93	99.72	0.52	4.73	87.17	27.22	858.93
INC	99.99	99.79	0.42	3.80	89.37	22.56	658.57
PSO	98.73	98.24	3.19	20.21	99.81	0.06	0.39
SMC	97.24	97.27	4.95	32.50	97.07	6.17	55.40
ISMC	98.87	98.87	2.05	5.65	98.84	2.45	9.30
ANN	99.96	95.25	8.61	147.77	99.46	0.41	0.44
SAISMC	99.99	99.89	0.07	0.67	99.82	0.13	2.60

VII. CONCLUSION

This paper presents the comparative performance of classical MPPT, meta-heuristic MPPT, and robust controllers under sudden irradiance changes and under addition of stochastic noise to the parameters. The seasonal adaptive integral sliding mode controller(SA-ISMC) is designed and integrated with the PV panel and DC-DC converter for performance of MPPT enhanced. The simulation results showed the SA-ISMC outperforms a higher efficiency, almost zero IAE and minimum ISE as compared with the industry standard P&O, INC, and SMC methods. The SA-ISMC showed most robust against sudden irradiance change and stochastic noise addition to the collected data. The SA-ISMC outperforms all MPPT algorithms with the highest efficiency(99.81%), minimum IAE(0.13), and ISE(2.60). Also the SA-ISMC demonstrated faster convergence speed a s compared with other MPPT methods. Those performance improvements are crucial for PV system stability and maximum energy harvest for regions like Ethiopia characterized by a variable solar data.

VIII. FUTURE WORKS

The future works for this paper are demonstrate under real world scenarios like partial shading conditions and sensor noise. Also scaling to PV+wind, PV+hydro to a larger microgrids and analyze the reduction of sampling time and computation in a energy efficient way.

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