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Research Article

Performance Evaluation of Regression-Based MPPT Algorithms Using Inverse SEPIC Converter under Partial Shading

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ABSTRACT

Numerous green energy resources, including solar, wind, bio, and hydropower, have garnered significant attention as effective alternative energy sources. Particularly beneficial to society and the economy, solar photovoltaic systems (SPVS) are the most preferred resource. Unfortunately, because of shadowing situations and fluctuating loads, these systems are unable to maximize power extraction under changeable irradiance. Many Lower Peak Power Points (LPPPs) and Global Peak Power Points (GPPPs) on their power voltage characteristics (P-VC) arise as a result of PSC. Therefore, these systems employ Maximum Power Point Tracking (MPPT) approaches. This work implements and experimentally evaluates two supervised learning MPPT schemes, Support Vector Regression (SVRT) and Linear Regression Based Technique (LRBT), for stand-alone photovoltaic systems under partial shading, using an inverse SEPIC converter. The main novelty is a hardware-aware, real-time evaluation of a computationally light LRBT MPPT on an inverse SEPIC topology, and a comparative analysis against SVRT on metrics relevant to practical deployment, including computational complexity, tracking time, output power or current, and tracking efficiency, under realistic partial shading conditions. Unlike prior ML studies that rely on simulation or heavy models, LRBT demonstrates fast convergence and very low computational cost suitable for microcontroller implementation. In MATLAB/Simulink experiments on a 2×2 PV array and inverse SEPIC converter, LRBT achieves a mean tracking efficiency of 98.3% (±0.25%), reduces tracking time to approximately 0.10 s (variance 0.0008 s), and improves delivered power by about 2.0–3.0% relative to SVRT under the tested shading patterns. LRBT's model size and prediction speed make it significantly more suitable for low-cost real-time hardware compared to SVRT.

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1. INTRODUCTION

Researchers are compelled to explore alternative energy sources as the world's energy consumption grows, the accessibility of fossil fuels diminishes, and pollution levels rise. Solar power generation with SPVS is the most encouraging renewable energy source, which does not require any rotating parts and is environmentally friendly. It simply requires freely available sunlight. One of the main drawbacks of these systems is their strong reliance on solar irradiation, which causes a variable power yield at the output. When the SPVS receives uniform irradiance, its P-VC has a single peak known as GPPP. As illustrated in Fig. 1, several MxPP occur on the P-VC when PSC cause the SPVS to receive uneven illumination. The lesser peak values in a P-VC are referred to as LPPP, while the uppermost power peak is referred to as GPPP, except the highest peak. In order to attain the true GPPP during PSC, MPPT systems are sometimes combined with SPVS. One of the issues that concern MPPT designers is an algorithm's capacity to pursue GPPP during a shading instance. One of the primary reasons for multiple power peaks (LPPP and GPPP) with irregular trajectories is partial shading. The P-VCs are shaped in such a way that the MPPT can no longer track the real GPPP.

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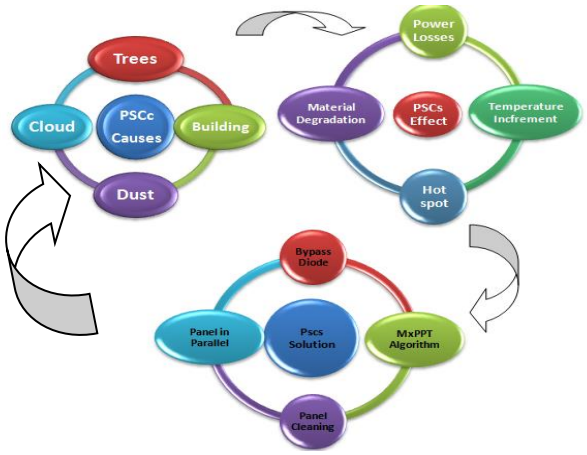

Figure 1. PSC Root causes effect and solution

General MPPT approaches, such as Hill climbing [Rawat et al. 2013], PnO [Piegari et al. 2017], HCg [Piegari et al 2017], and INCA [Podder et al. 2019], are proven more efficient in calculating real MXmPP for homogeneous irradiance with a noticeable peak on P-VCs. Nevertheless, these methods often belong to one of the LPPPs under PSC and fail to guarantee world-wide convergence, leading to power loss [Podder et al. 2017; Ishrat et al. 2023; Mosa et al. 2017]. Later on, these methods have been modified to track GPPP under PSC [Podder et al. 2019, Ishrat et al. 2023, Mosa et al. 2017, Kamarzaman et al. 2014, Mustafa et al. 2020]. Researchers have focused on various artificial intelligence-based MPPT strategies to address complex problems that resulted from PSC [Mosa et al. 2017, Karami et al. 2017, Liu et al. 2014, Mohapatraet . al. 2017]. The GPPP can be determined using a metaheuristic algorithm, with MxPPTMPPT identified as an optimization problem. Based on the population approach, a number of swarm intelligence [Nugraha et al. 2017, Hayder et al. 2020, Ahmed et al.2014] and bio-inspired [Abu et al. 2020, Belghith et al. 2016, Rezk et al. 2017] methods were examined. Moreover, the aforementioned modifications made to improve their performance were reported [Pilakkat et al. 2020, Martínez et al. 2021]. ANN [Tey et al. 2018], evolutionary algorithms [G. Tandel et al. 2016], and FLC [Takun et al. 2011,Tey et al. 2018] were also utilized in PSC to monitor GPPP. In the past few years, numerous hybrid approaches have also been reported, combining two or more MPPT procedures to leverage their respective features [Batarseh et al. 2018, Priyadarshi et al. 2019, Manickam et al. 2016]. By combining the traditional method with the bio-inspired (INC-DFO) approach, the authors [Sarwar et al. 2022] demonstrated a novel idea for GPPP tracking under PSC with an average efficiency of 99.92%. Another study [Sharmin et al. 2022], the Bayesian network-based method is suggested for maximizing the total power yield of the PV arrangement while minimizing steady-state fluctuations and monitoring time. The proposed strategy is 99% accurate at following the GPPP within 2 s and responds to load variations within 0.1 s. A SEPIC converter is used in [Memaya et al. 2019] and simulated on MATLAB. A localized version of the SVM and ELM supervised MLA [Du et al. 2018] eliminates the necessity for regular parameter training. Takuri et al. [Takruri et al. 2020] also employed SVM to predict the optimal reference voltage of a photovoltaic setup in the presence of changing load conditions, temperature, and solar irradiance. Ishrat et al. compared two regression-based techniques for MPPT of SPVS [Ishrat et al. 2023]. A comparative analysis of ML-based MPPT techniques was proposed by different scholars in [Ishrat et al. 2024a; Ishrat et al. 2024b; Nkambule et al. 2020; Sun et al. 2019]. The authors [AI et al. 2024] provides a comprehensive review of advanced metaheuristic and hybrid MPPT algorithms for solar photovoltaic power generation, identifying Grey Wolf Optimization and Jaya-Differential Evolution as leading techniques for maximizing power extraction under variable conditions. Its major finding is that these algorithms outperform conventional methods, especially when validated experimentally on industrial-scale PV systems. However, the study is limited by a lack of uniform test conditions, which makes direct performance comparison and practical recommendations challenging. In terms of computational complexity, hardware implementation feasibility, and computational time, each of these intelligent strategies varies from the others. Table 1 provides an examination of newly published intelligent techniques based on significant MPPT features.

The following are the main goals of the current study:

- Software deployment of standalone SPVS using inverse SEPIC and resistive load along with LRBT and SVRT MPPT techniques.
- Performance appraisal in real time of two MPPT techniques (SVRT and LRBT) under varying environmental conditions.
- Comparative evaluation of SVRT and LRBT on several metrics when monitoring GPPP in test scenarios.

Novelty of work: Imagine a home solar energy system installed on a rooftop in an area with fluctuating weather patterns, including intermittent shade from adjacent trees and structures during the day. Conventional MPPT controllers frequently face difficulties in optimizing power extraction during dynamic shading because of various local maxima in the power voltage curve created by shading. In such a case, the suggested LRBT MPPT controller employs regression machine learning to quickly and precisely determine the global maximum power point in real time. For example, when the shadows of a moving cloud diminish sunlight intensity on a section of the array, the controller promptly modifies the duty cycle of the SEPIC converter to follow the new optimal operating point within a short duration. This rapid reaction reduces power loss, resulting in an average power efficiency exceeding 98% even under varying conditions.

This work's novelty can be summed up as a set-theoretic presentation and comprehensive performance evaluation emphasizing technical datasheet-style reporting of the primary characteristics of two distinct MPPT techniques. The novel points of this research are as follows:

a) Lightweight LRBT suitable for microcontroller implementation due to the simplicity of the model.
b) First real-time evaluation on inverse SEPIC topology in this configuration under varying environmental conditions.
c) Quantitative comparison of SVRT and LRBT that highlights LRBT's favorable trade-offs in tracking time, computational complexity, and output power in real-time-like tests.

Table 1 Review of the latest work to track GPPP under PSC.

Author(Reference)	AI-MPPT	Hardware Used	Converter	Software used	Error	Tracking Duration	Maximum efficiency
Keyrouz et al. 2018	BNN-MPPT	Arduino & DSP	Boost	Matlab	Mean absolute error=4%	1.76s	97.89%
Memaya et al. 2019	DE-MPPT	PVUE125MF5N	SEPIC	PowerSim	Error Margin=1%	2s	99%
Du. et al 2019	SVM&ELM	R-305E-WHT-D	Boost	Matlab	Mean Absolute error=0.083	.02sec-.15sec	94.52%
Radjai et al. 2014	MLVR-P&O	dSPACE DS1104	Buck	Python	Error Margin=0.5%	.08sec-.2sec	99.8%
Sharmin et al. 2022	BNN-P&O	ZM-A-M-100	Boost	Matlab	MSE= $2.87*10^{-3}$	Not Specified	99.594%
Kalogerakis et al. 2020	Q Learning	DSP	Boost	Matlab	MSE=0.1-1%	.04sec-0.2 sec	99.3-99.6%
Mahesh et al. 2022	DTR	Arduino & DSP	Boost	Matlab	Low RMSE	0.6s	93.99%
Farayola et al. 2018	LIR	1STH-215-P module	Cuk	Psim	RMSE=5.5339e-7	.05sec-.2sec	73.24%

LRBT outperforms other intelligent approaches documented in the literature in terms of T, E, CC, OP, and OC, according to test validation and relative analysis conducted in real-time surroundings. The remaining sections of this manuscript are organized as follows: The problem formulation is illustrated in Section 2, and the two MPPT AI approaches selected to analyze their GPPP performance under PSC are presented in Section 3. Section 4 provides the complete experimental setup. Section 5 discusses the effectiveness and outcomes of the chosen MPPT techniques. Section 6 outlines the study's challenges and expanded scope, while Section 7 offers the conclusion.

2. Modeling of SPVS

An SPVS is made up of several solar panels consisting of solar cells connected in parallel and series. Since the single diode model (SDM) requires fewer parameters for accurate modeling and imposes less computational overhead, it is used to design and analyze SPVS. Figure 2 depicts the widely used SDM of an SPVS. The SPVS can be mathematically modeled under uniform irradiance using Functional Eq. (1), and its I-V relationship can be expressed as follows:

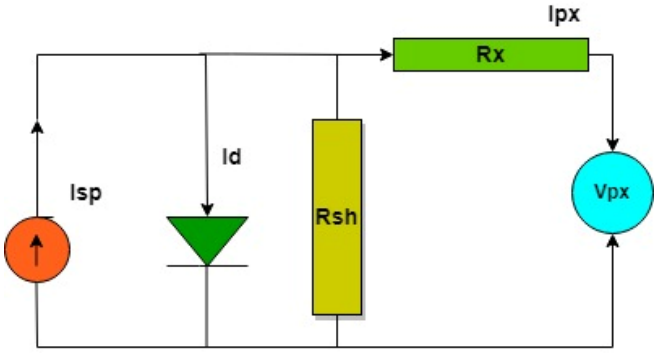

Figure 2. SDM of SPVS

$$Ip = Isp - Id - (Vpx + IpxRx)/Rp \quad (1)$$

$$Ipx = NpIsp - NyId - \frac{Vpx + IpxRxnz}{Rp * nz} \quad (2)$$

Where nz= Ny/Np

$$Id = Is(e\frac{q(Vpx + IpxRx)}{AKTNy} - 1) \quad (3)$$

Figure 1 illustrates the various factors that contribute to deviations in incident radiation (PSC) on different modules within the SPVS, including reduced FF and power loss. Under PSC, the harnessed power of several modules in the array will drastically drop, resulting in hotspots and unbalanced conditions throughout the system. This problem is mitigated by using bypass diodes. Moreover, temperature affects the SPVS's output, so different cooling strategies are employed to address this issue [Bayrak et al. 2020, Bayrak et al. 2019, Sattar et al. 2022]. By adding various materials, the structure can also achieve improved energy conversion [Khan M. et al. 2022].

This simulation is carried out on a 2×2 SPVS array, as displayed in Figure 3, using the SPVS module under the conditions mentioned in Table 2. To reduce the adverse effects that occur in SPVS due to PSC, this study evaluates MPPT techniques under three test conditions, as listed in Table 3, with SEPIC converters applied in each condition individually. Figure 3(a) shows the SPVS under PSC1, while Figures 3(b) and 3(c) show the SPVS under PSC2 and PSC3, respectively.

Table 2. Specifications of a user-defined unit solar cell model in Matlab/Simulink

Parameter	Value
OCV	7.5V
Isc	2.2A
Vmp	6V
Imp	1A
Pm	6W
Temperature Coefficient(Tc) of Voc (% /deg c)	-0.36099
Tc of Isc (% /deg c)	0.102
Ir	1.5A
Rsh	9.92ohm
Rx	0.035ohm

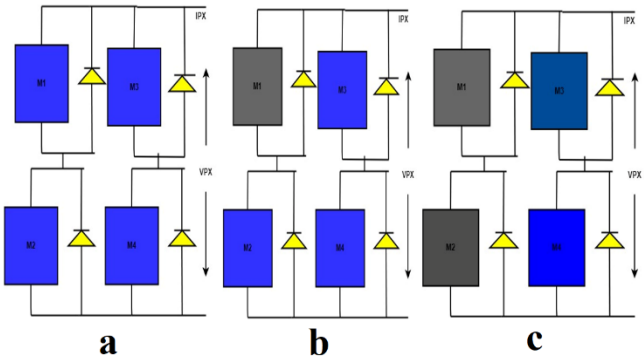

Figure 3. (a) PSC1, (b) PSC2 & (C) PSC3

Table 3. Operating Condition

Condition	Environment Condition
PSC1	(1000W/m^2,& 25 °C)
PSC2	(800W/m^2,& 25°C)
PSC2	(800W/m^2, & 25°C)

3. AI MPPT Techniques

3.1. Support Vector Machine Regression (SVRT)

Regression tasks, where the objective is to predict a continuous target variable instead of class labels, can also be implemented using SVRT. The main goal of SVR is to find a function, or a hyperplane in the feature space, that most accurately captures the relationship between the input parameters and the continuous target variable. The objective of SVR is to identify a hyperplane, also known as a regression line, that minimizes the difference between the predicted and actual target values while adhering to a predetermined margin. Minimizing the cost function, as provided by the equation, is the aim of SVRT (Kumar Panda et al., 2023, Beers 2024, Alpaydin, n.d., Mohri et al., 2018, Rasmussen, 2004, Awan et al., 2021).

$$J(w,B,,\epsilon,\epsilon') = ½ \bmod \{w\}^{2} + C\sum_{i=1}^{n}(\epsilon + \epsilon') \quad (5)$$

W represents the weight and B represents the bias value, ε and ε' are the margin variables allowing for error, and C is the regularization parameter that controls the trade-off between error and the margin variables.

The regression function using SVRT is:

$$F(x)=W^{T}+B \quad (6)$$

where x is the input feature vector.

The new predicted values should lie within the margin, so limiting conditions are applied, as given in the equations:

$$Yi - f(xi) \leq \delta + \epsilon i \quad (7)$$

$$f(xi) - Yi \leq \delta + \epsilon i' \quad (8)$$

where Yi is the target value for the ith data point, δ is the acceptable error, and ϵi, ϵi' are slack variables.

A dual problem W(β, β') is created using Lagrange multipliers (β, β') for each constraint. The dual problem is to maximize the following equation:

$$W(\beta,\beta')=\sum_{i=1}^{N}(\beta i - \beta i') - \frac{1}{2}(\sum_{i\,j=1}^{N}(\beta i - \beta i')\beta j - \beta j')\,(xi, xj) \quad (9)$$

Subject to constraints:

$0 \leq \beta, \beta i' \leq C$

$$\sum_{i=1}^{N}(\beta i - \beta i') = 0 \quad (10)$$

The weight vector, w, can be computed by

$$w = \sum_{i=1}^{N}(\beta i - \beta i')(xi1, xi2) \quad (11)$$

$$b = Ys - \sum_{i=1}^{N}(\beta i - \beta i')(xi1, xi2) \quad (12)$$

To predict a new target value, the SVRT function is given as follows:

$$F(Xnew) = w^{T}Xnew + B \quad (13)$$

Table 4 presents the error estimation during the training and testing phases using the SVRT algorithm model.

Table 4. Error analysis of the SVRT Model

Error(Validation)			Error(Testing)		
RMSE	**MSE**	**MAE**	**RMSE**	**MSE**	**MAE**
0.0689	0.0047472	0.05806	0.06912	0.00472	0.0559
Prediction 1800obs/sec					**Speed**
Training 12.174sec					**Time**
Model 4KB					**Size**

3.2. Linear Regression Algorithm based technique (LRBT)

By applying a linear equation to empirical data, linear regression is a widely used supervised ML approach for modeling the relationship between a dependent variable (target) and one or more independent variables (features). It is a simple yet effective algorithm that is commonly applied in forecasting, prediction, and analyzing variable relationships. The linear regression model represents the relationship between the target variable (Y) and the features (X) as a linear equation (Kumar Panda et al., 2023; Beers, 2024; Alpaydin, n.d.; Mohri et al., 2018; Rasmussen, 2004; Awan et al., 2021).

$$Yx = £_o + £_1X_1 + £_2X_2 + \ldots + £_3X_n + \varepsilon \quad (14)$$

Where £0 is the intercept value and £1, £2 are the coefficients that indicate the unit change in Yx when there is a change in X, and ε represents the acceptable error.The cost objective function for LRA is given in the following equation, which should be minimized:

$$MSE = I/N \sum_{i=1}^{N}(Y' - Yx)2 \quad (15)$$

where N is the number of data points, Y' is the predicted target value, and Yx is the actual value. The main goal is to determine the coefficients that minimize the error.Table 5 presents the error estimation during the training and testing phases using the LRBT algorithm model.

Table 5. Error analysis of the LRBT Model

Error(Validation)			Error(Testing)		
RMSE	**MSE**	**MAE**	**RMSE**	**MSE**	**MAE**
0.01642	0.0047472	0.0143056	0.01644	0.0003135	0.014314
Prediction 4800obs/sec					**Speed**
Training 5.0871sec					**Time**
Model 4KB					**Size**

3.3. Proposed AI-MPPT Algorithm

Authors use the SVRT and LRBT methods to track the MXmPP of a SPVS. The steps of the proposed MPPT algorithm are listed below. Figure 4 illustrates the flow chart of the proposed MPPT algorithm.

i. Evaluate the SPVS voltage Vpx and current Ipx for the given radiation and temperature conditions.
ii. Compute the instantaneous SPVS power Px.
iii. Estimate the future maximum current Im_pp using the AI-MPPT model for the incident illumination and temperature.
iv. If the instantaneous current Ipx < Im_pp, increase Ipx by adjusting the duty cycle Dd.

v. If the instantaneous current Ipx > Im_pp, decrease Ipx by adjusting the duty cycle Dd.
vi. Repeat the procedure until Im_pp = Ipx.
vii. Compute Px when the target is achieved and display the Pmax of the SPVS.

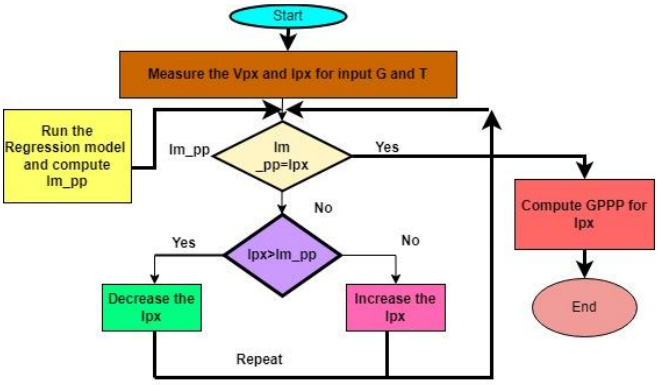

Figure 4. MPPT Algorithm Flow Chart

3.4. Simulation setup

A prototype experimental setup is used to test two AI approaches (Fig. 5). A standalone SPVS prototype is designed using four user-defined PV panels connected in a 2×2 series-parallel configuration. An inverse SEPIC converter is employed to evaluate the performance of each technique. The method under consideration is tested for performance under PSC by integrating a resistive load into the SPVS. PSC are induced in the SPVS under non-uniform irradiance conditions using variable illumination. Figure 5 presents the block diagram of the MPPT arrangement.

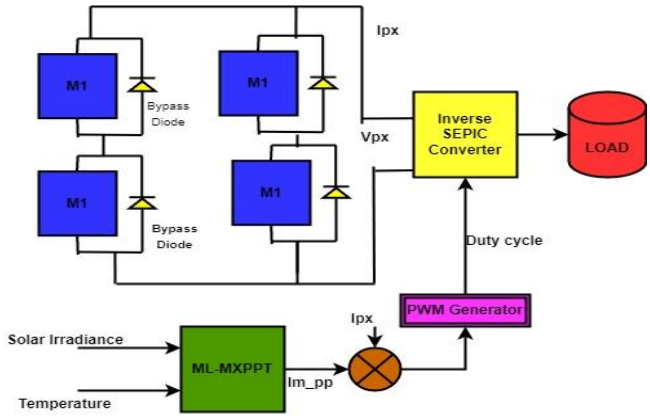

Figure 5. Block diagram of the MPPT

4. Inverse SEPIC DC converter

The SEPIC converter, also known as a zeta converter, is used to increase or decrease Vin to a regulated value using a simple and low-cost mechanism. The DC conversion ratio is given by Eq. (16) as follows:

$$Vout/Vin = D_n/(1 - D_n) \quad (16)$$

If D_n>0.5, the SEPIC operates in boost mode; otherwise, it operates in buck mode. The inverse SEPIC converter design is discussed in [Putri et al., 2021, Moon et al., 2022, Gökkuş & Endiz, 2024], with its component specifications listed in Table 6.

Table 6. Specifications of the inverse SEPIC DC converter parameters

Parameter	Value
Vin-min	6V
Input Voltage Maximum	16 V
Output voltage Maximum	15V
Output current Minimum	1.2A
Output current Maximum	1.8 A
Output Power Minimum	18W
Output Power Maximum	24W
L1	0.165mh
L2	0.165mh
Ro	9.3ohm
C1&C2	88microfarad
f	100Khz
Change in inductor current	0.1
Change in capacitor voltage	0.4

5. Results and Discussion

Authors first evaluate the performance of MPPT approaches in tracking the GPPP under variable environmental conditions with a fixed load. The performance of each MPPT method (LRBT and SVRT) on a standalone SPVS with a 2×2 SPV configuration, as shown in Fig. 5, is simulated in terms of output power, current, tracking time, and tracking efficiency. Each method is simulated in Matlab/Simulink under three varying solar illumination conditions, as summarized in Table 7. In PSC-1, all panels receive the same illumination intensity of 1000 W/m². In PSC-2, one SPV is shaded, receiving 800 W/m². In PSC-3, the SPVS is illuminated at 600 W/m². Figure 6 shows the voltage, current, and power under STC for the 2×2 SPVS. Figure 7 shows the load output voltage, which remains almost constant across all shading patterns. Figures 8, 9, and 10 present the panel output current, SEPIC converter output current using LRBT, and SEPIC converter output current using SVRT under PSC-1. Figures 11, 12, and 13 show the corresponding currents under PSC-2. Figures 14, 15, and 16 depict the currents under PSC-3 for panel output current, LRBT converter output current, and SVRT converter output current, respectively.

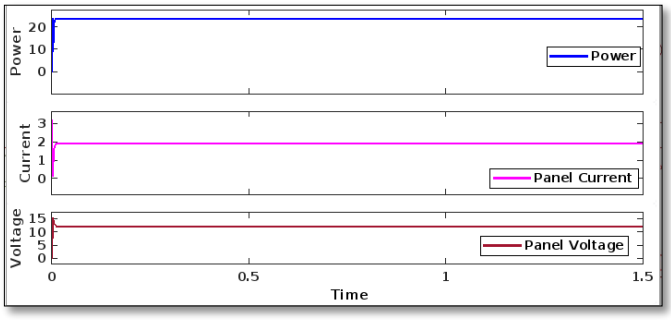

Figure 6. 2*2 SPVS's voltage, current, and power under (1000Watt/m², 25°C)

Table 7. Simulation Result of 2*2 SPVS

Solar irradiance	Vin (v)	Iin (A)	Vout (v)	Iout (A)	η (Pout/Pin)*100	Vin (v)	Iin (A)	Vout (v)	Iout (A)	η (Pout/Pin)*100
	LRBT					SVRT				
PSC1(1000W/m^2,25 °C)	12	2.04	13.79	1.74	99.97	12	2	13.79	1.705	97.96
PSC2(800W/m^2, 25°C)	12	1.805	13.79	1.553	98.87	12	1.805	13.79	1.513	96.32
PSC3(600W/m^2, 25°C)	12	1.61	13.79	1.370	98.39	12	1.61	13.79	1.35	96.96

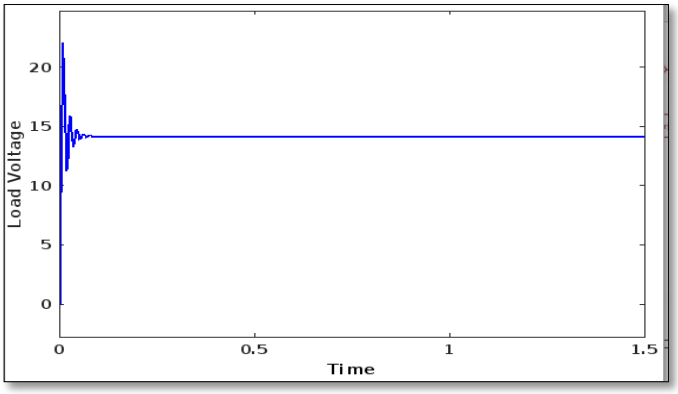

Figure 7. Load output voltage under (1000Watt/m^2, 25°C)

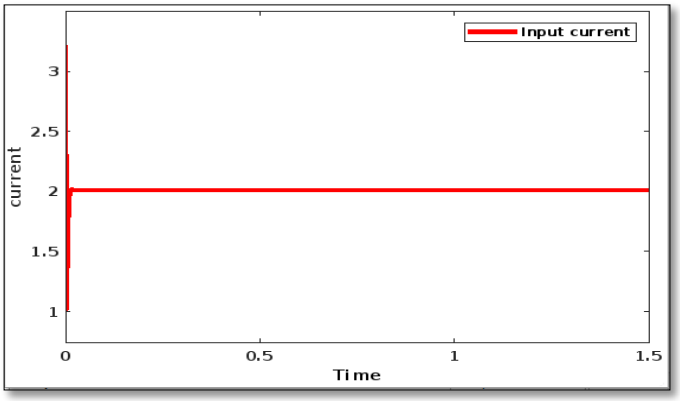

Figure 8. Panel output current under (1000W/m^2, 25°C)

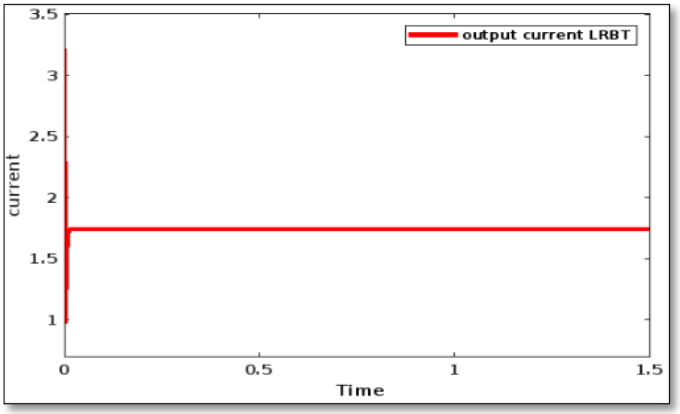

Figure 9. Load output current under (1000W/m^2, 25°C) using LRBT

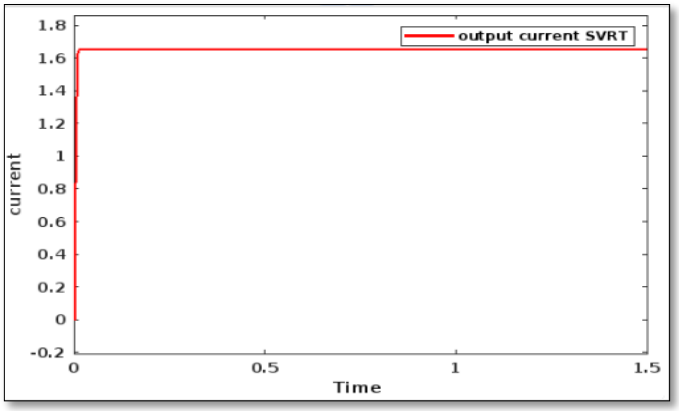

Figure 10. Load output current under (1000Watt/m^2&25°C) using SVRT

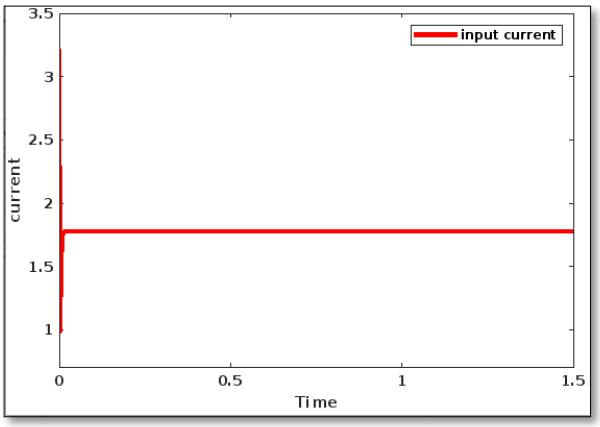

Figure 11. Panel output current under (800W/m^2&25°C)

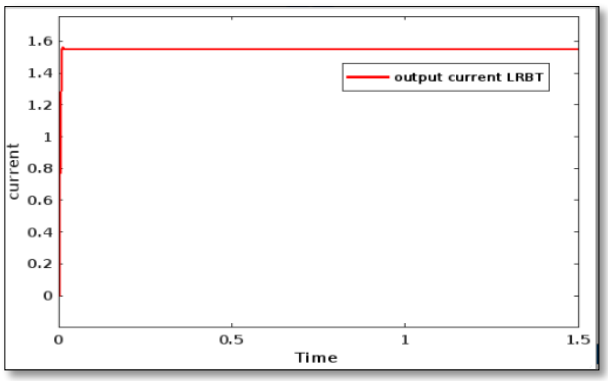

Figure 12. Load output current under PSC2(800Watt/m^2, 25°C) using LRBT

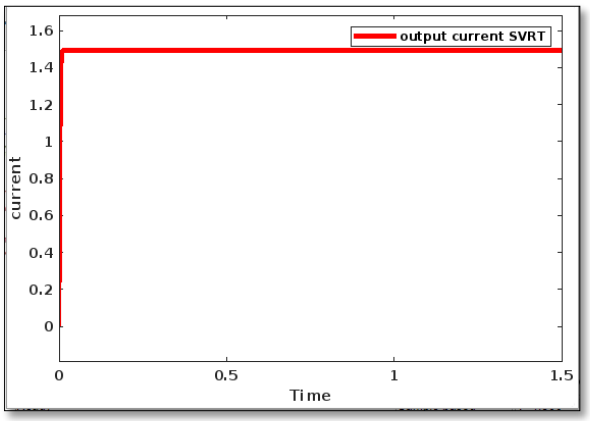

Figure 13. Load output current under PSC2 (800Watt/m^2&25°C) using SVRT

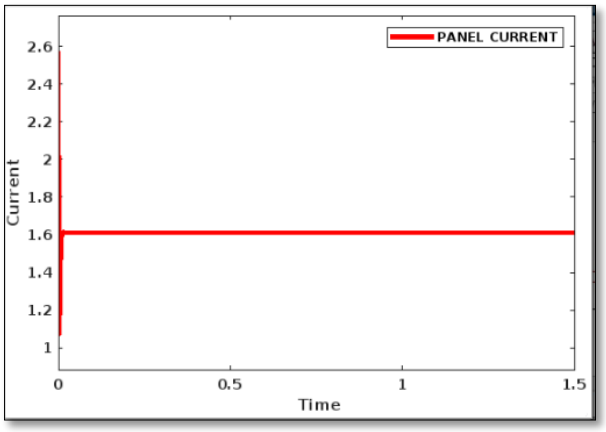

Figure 14. Panel output current under PSC2(600Watt/m^2&25°C)

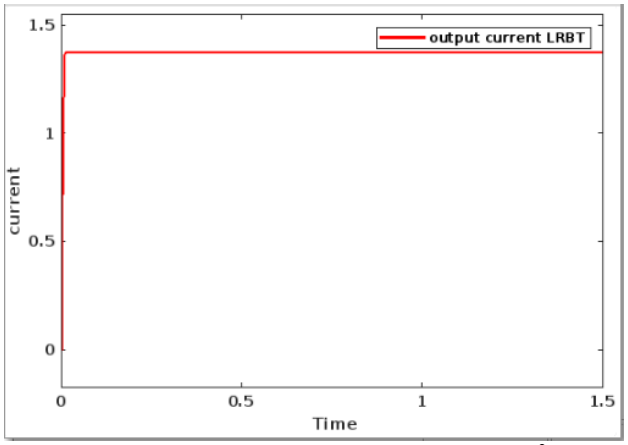

Figure 15. Load output current under PSC2(800Watt/m^2, 25°C) with LRBT

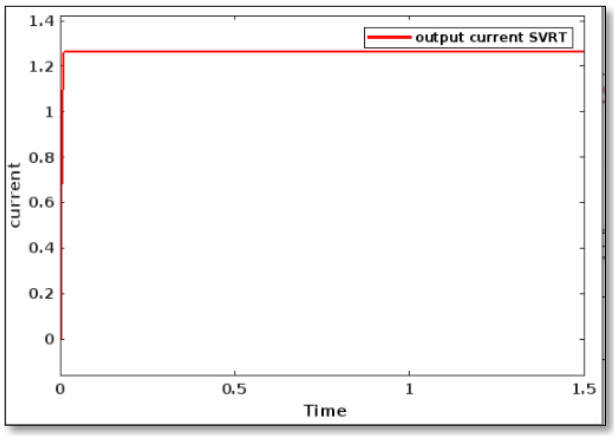

Figure 16. Load output current un PSC2(800Watt/m^2, 25°C) with SVRT

5.1. Efficiency of Controller under varying weather conditions

Equation (17) is used to calculate the power efficiency of both the conventional and proposed controllers to evaluate the effectiveness of the LRBT-MPPT controller.

$$\text{Efficiency}=(\text{Pout}/\text{Pin})*100 \quad (17)$$

Where Pout is the average power output of the SEPIC controller under all operating conditions, and Pin is the steady average input power to the controller. Figure 17 illustrates the tracking efficiency under PSC-1, PSC-2, and PSC-3. The LRBT-MPPT controller demonstrates the highest tracking efficiency under varying climatic conditions.

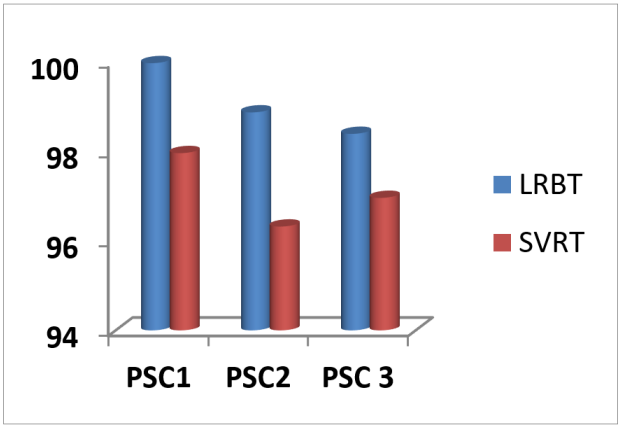

Figure 17. Comparison of tracking efficiency under PSC-1, PSC-2, and PSC-3

6. Conclusion

A sophisticated LRBT-MPPT controller was proposed using a SEPIC converter. The performance of this controller was verified through comparison with the SVRT approach. The results indicate that the proposed method is more advantageous due to its features, which include rapid convergence, improved efficiency exceeding 98% in all tested shading scenarios, and minimal variations at the steady state. It significantly reduces oscillations under equilibrium conditions and demonstrates excellent dynamic performance. In this paper, a novel controller built using regression-based machine learning was presented. The key points are as follows:

I. LRBT achieved a mean efficiency $\eta = 98.3\% \pm 0.25$, compared to SVRT.

II. The proposed system operates in real-time and provides high tracking speed, with a tracking time of 0.10 s (variance 0.0008 s), a low root mean square

error (RMSE) of 0.01689, and minimal steady-state fluctuations.

III. The LRBT model size is 4 KB, with a prediction speed of approximately 4800 observations per second, making it suitable for deployment on microcontrollers.

Future Work: Leveraging the promising results of the LRBT-MPPT controller, subsequent studies may explore several avenues to enhance performance and expand applicability:

- Hardware Deployment and Real-Time Assessment: Transitioning from MATLAB simulations to actual hardware implementation with real-world sensors and converters will validate the controller's robustness and performance under practical conditions, including noisy environments and imperfect components.
- Adaptation to Various Climate Scenarios: Enhancing the model to flexibly respond to different weather patterns, seasonal changes, and harsh conditions through online learning or adaptive machine learning techniques.
- Investigation of Hybrid or Ensemble Machine Learning Models: Combining regression with other machine learning or deep learning approaches to improve tracking accuracy and speed, particularly under rapidly fluctuating irradiance conditions.

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NOMENCLATURE

PV	Photovoltaic
SPVS	Solar Photovoltaic System
MPPT	Maximum Power Point Tracking
P-VC	Power Voltage Characteristics
MxPP	Maximum Power Point
SEPIC	Single-Ended Primary Inductor Converter
PSC	Partial Shading Condition
GPPP	Global Peak Power Point
LPPPs	Lower Peak Power Point
V_in	Input voltage (V)
I_in	Input current (A)
V_out	Output Volatge
I_out	Output current
Pout	Output power (W)
η	Tracking efficiency (%)
CC	Computational Complexity
T	Tracking Time
OP	Output Power
OC	Output Current
Rsh	Shunt Resistance, Rx: Series Resistance
Id	Diode Current
Isp	Incident solar panel current
Ipx	shunt leakage current
Ip	Output Current
Is	Saturation Current
nz	array configuration ratio
Ny	Series Module
Np	Parallel module
A	Diode ideality factor between 1 or 2
K	Boltzman constant 1.381×10^{-23} J/K
T	Cell temperature in K
Pno	Perturb & Observation algorithm
HCg	Hill Climbing algorithm
INCA	Incremental Conductance algorithm
FLC	Fuzzy Logic Control
INC-DFO	Incremental Conductance – Dragonfly Optimization
LRBT	Linear Regression Based Technique
SVRT	Support Vector Regression Technique
ELM	Extreme Learning Algorithm
DTR	Decision Tree Regression
ANN	Artificial Neural Network
BNN	Bayesian Neural Network
MVLR	Multiple variable linear regression algorithm
SVM	Support Vector Machine
DE	Differential Evolution based algorithm

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