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Original Article

Enhancing Solar Photovoltaic Systems through Advanced MPPT Control: A Comparative Analysis of AI-Based Techniques and A Novel ML-Based SVR Model for Optimal Performance and Stability

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Abstract *- This paper addresses the critical need to achieve consistently stabilized output power in solar Photovoltaic (PV) systems, which is achieved through the implementation of Maximum Power Point Tracking (MPPT) mechanisms. Recent research findings consistently highlight the superiority of MPPT controllers employing Artificial Intelligence (AI) techniques over traditional MPPT methods. In response, this study proposes a novel approach that integrates Machine Learning (ML), specifically a Support Vector Regression (SVR) MPPT controller. The core objective is to rigorously benchmark the effectiveness of the suggested ML-based SVR MPPT controller against well-established AI-based MPPT counterparts. This comparative analysis spans vital performance indicators, including Mean Efficiency (ME), Settling Time (Ts), Rise Time (tr), Peak Time (Tp), and Percentage Overshoot (PO). Through meticulous investigation, this paper not only contributes to the ongoing evolution of modern MPPT techniques but also offers intricate insights into the distinct advantages of AI-based and ML-based strategies in significantly enhancing the overall performance and adaptability of MPPT controllers. This analysis employs a single junction Gallium Arsenide (GaAs) solar cell known for its elevated efficiency in constructing a 2KW solar panel. Additionally, an optimized DC-DC boost converter is integrated into the setup. The SVR tool is trained and tested using diverse temperature and irradiance data sets to detect the PV panel's maximum power and voltage under specific conditions. The optimum DC-DC boost converter's Duty cycle (D) control for MPPT is made by the detected values from the SVR algorithm. An energy-efficient GaAs cell-based PV system is enabled using the proposed ML-based SVR MPPT controller, which forces the PV panel to operate the detected Maximum Power Point (MPP). The proposed SVR algorithm offers better stability and operates at 96.6% of mean efficiency, irrespective of climatic changes. This work is further extended for comparison with Perturb and Observe (P&O) and Fuzzy Logic Control (FLC) to evaluate the effectiveness of the proposed work.*

Keywords *- Artificial Intelligence, Efficiency, Machine Learning, MPPT, Support Vector Regression, GaAs.*

1. Introduction

Global emissions of carbon dioxide from the burning of fossil fuels range a radical level after a few decades. So, developed countries have started investments to replace coal with renewable energy resources [1]. The most advanced in renewable energy resources is photovoltaics, which uses semiconductors to convert solar radiation into electricity. Researchers were seriously concentrating on increasing the efficiency of solar panels by considering the economic factor. MPPT system is an essential tool in photovoltaics to track the maximum PV power at all times, irrespective of climate changes. Several MPPT technologies are available in the PV market, each having its own merits and demerits. The most familiar traditional MPPT methods, such as P&O, incremental conductance, constant voltage, and short circuit current, are used. The AI-based MPPT controllers such as Fuzzy Logic Control, Artificial Neural Network control and ANFIS are listed in the literature. Recently, Machine learning-based MPPT controllers such as reinforcement learning, Random Forest methods, Decision Trees [14], and Support Vector Regression (SVR) algorithms [15] have been the most compatible methods to handle non-linear PV data. Machine Learning algorithms increase the accuracy and speed of the MPPT controller [2].

The new technologies must overcome the older methods of MPPT control in view of studying the past, updating the present and estimating future requirements. Recently, regression techniques have been highlighted as an optimal tool for MPPT control because of their higher convergence stability and fast computing when compared with older meta-heuristic techniques [3]. P&O [12] and the Incremental Conductance method [11] are the most familiar traditional MPPT controls. However, the settling time is too long during the dynamics in climate and also for sudden changes in load voltage. Also, the Artificial Intelligence (FLC and ANN) based MPPT controllers resolved the issues faced in traditional converters. However, the accuracy of FLC depends on the number of linguistic variables, number of iterations, and rule base selection, and it needs expert human participation to decide all these mandatory works. Similarly, the performance of ANN depends on the selection of layers and also neurons [4].

The SVR algorithm is highly sensible to predict the unknown parameters (I_{MPP} & V_{MPP}) from the known data set irradiance (I_G), real temperature (T_r), PV voltage (V_{pv}) and PV current (I_{pv}). SVR algorithm trains (75%) and tests (25%) the input known data set and converts it to a model database to predict the unknown output parameters. The converter is the most essential tool in a Photovoltaic system to operate it in an MPP irrespective of climate changes. The selection of converter depends on the output voltage requirements such as DC-DC buck, DC-DC boost, and DC-DC buck-boost, which are listed in the literature. The single junction higher efficiency Gallium Arsenide (GaAs) solar cells are utilized to construct the 2KW PV panel with an optimum DC-DC boost converter to control the Duty cycle (D). The DC-DC boost converter is carefully designed by considering the dynamics in climate conditions, load line criteria and Resistance at MPP [6]. GaAs solar cells generate up to 1.072V at Standard Test Conditions under air mass 1.5 global spectrum (Area = 100cm^2 and irradiance = 1000W/m^2, 25°C). It consumes less space because of its higher PV voltage, and it gains efficiency up to 29.1% [5].

The research gap is defined by the selection of higher efficiency thin-film GaAs solar cells, the modified DC to DC boost converter and SVR MPPT control. The GaAs solar cells-based PV systems have been introduced and successfully implemented by Atla devices (USA), but they are not familiar with the global PV market [19]. In this work, more importance is given to increasing the efficiency of the overall system in the selection of solar cells and MPPT controllers. Also, the existing traditional MPPT methods, such as P&O [18] and Incremental Conductance [18], exhibit prolonged settling times during dynamic climate conditions and sudden changes in load voltage. AI-based controllers (FLC and ANN) are struggling with some of the challenges, like introducing complexities related to the determination of linguistic variables [13, 20], iterations, and rule bases, and requiring expert human intervention. This reliance on human expertise leads to a constraint on the adaptability and autonomous decision-making capabilities of these systems.

The study emphasizes the importance of choosing an appropriate converter, particularly highlighting the careful design considerations related to climate dynamics, load line criteria and resistance at the MPP, as shown in Figure 8. The research concentrates on the potential findings using GaAs solar cell and Machine Learning SVR model to enhance accuracy, reduce settling time, minimize output parameter errors, and increase overall system efficiency. The work has been divided and organized into sections; section 2 includes PV system specifications and optimum DC-DC boost converter, section 3 provides the methodology and working procedure of SVR algorithm MPPT controller for PV system, section 4 deals with simulation and results discussion with the comparative analysis of P&O, FLC and SVR algorithm based MPPT control for a Photovoltaic system. The conclusion of this work is summarized in section 5.

2. Insight of Solar PV System

The higher efficiency GaAs solar cells are used to construct 2KW solar panels, as given in Table 1. The Machine Learning-based SVR model is proposed to control the Duty cycle of the optimum DC-DC boost converter.

2.1. Depiction of GaAs Solar Cell-Based PV Panel

Over the past few years, much research has been conducted in developing the micro-thin film solar cell because of its reduced weight, which is particularly important for space applications. Thin film light-absorbing semiconductor solar cell structures such as Cadmium Telluride (CdTe), amorphous Silicon (a-Si), Copper Indium Diselenide (CIS) and Gallium Arsenide (GaAs). The competition between silicon and gallium arsenide increases in terms of lightweight, flexibility and efficiency [7].

Among the other light-absorbing semiconductors, the GaAs come from the III/V compound semiconductor family, leading the global solar system market because of their unbeatable efficiency. The scientific model of GaAs solar cells is developed using a single diode equivalent circuit model, and it is used to obtain the performance characteristics for different temperatures, irradiance levels, series resistance, and shunt resistance values. The mathematical modelling of the semiconductor materials is done using the MATLAB platform in m-file. The practical one-diode equivalent circuit model of solar cells is shown in Figure 1.

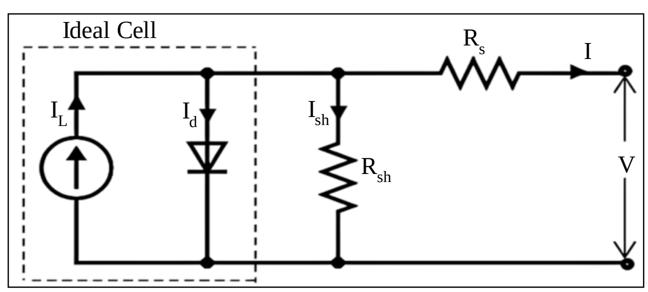


Fig. 1 Equivalent circuit model of a solar cell

The generation of internal current within the solar cell is Photon current (I_L) or light-generated current, and this current does not depend on the open circuit voltage. Applying Kirchhoff's current law to the node 'a', the PV cell current (I) will be given in Equation (1).

$$I = I_{sc} = I_{ph} - I_o\left(e^{\frac{q(V+I*R_s)}{nkT}} - 1\right) - \frac{V+(I*R_s)}{R_{sh}} \text{ for } V_{oc} = 0 \quad (1)$$

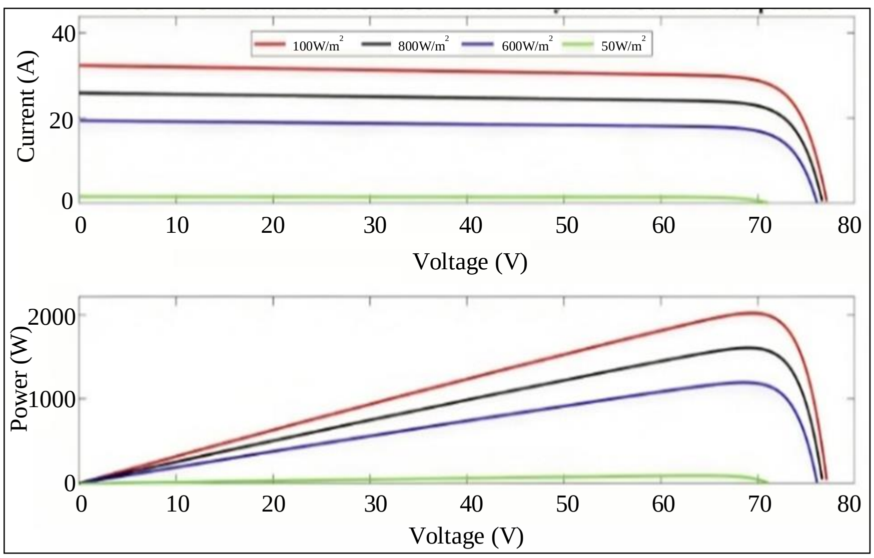
The open circuit voltage solar cell is a vital function of temperature, and it depends on the nature of the semiconductor material. The open circuit voltage of a solar cell at zero cell current is given in Equation (2),

$$V = V_{oc} = \frac{nkT}{q}\ln\left(\frac{I_L}{I_o} + 1\right) \text{for } I_{sc} = 0 \qquad (2)$$

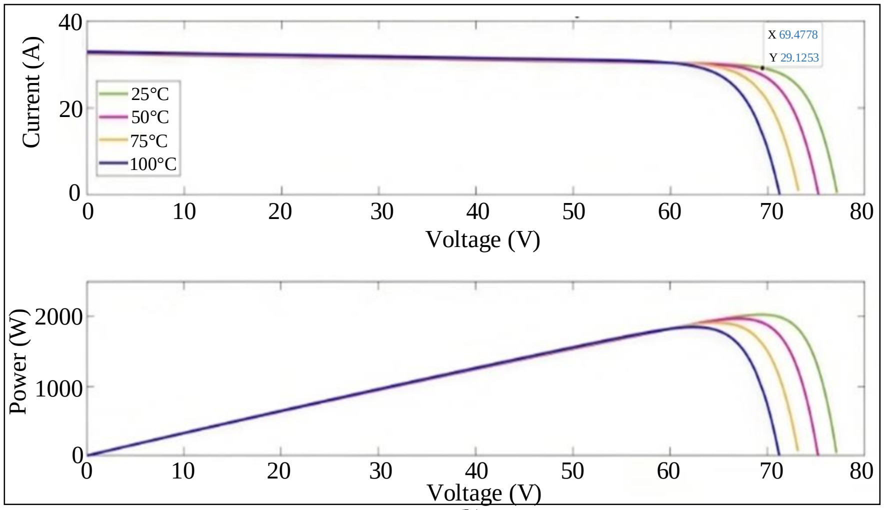
This single-cell model is utilized to construct a 2KW PV array, and then its performance is evaluated under different temperature and irradiance levels. It is observed that single junction GaAs PV array develops 2025W for the cell description given in Table 1.

Table 1. PV panel specifications

S. No.	Parameters	Range
1	Open Circuit Voltage	1.072V
2	Maximum Cell Voltage	0.964V
3	Number of Cells per Module	72
4	Open Circuit Voltage/Module (V_{oc})	77.18V
5	Short Circuit Current/Module (I_{sc})	3.241A
6	Voltage at MPP/Module (V_{mpp})	69.40V
7	Current at MPP/Module (I_{mpp})	2.916A
8	Number of Parallel Strings	10
9	Number of Series Modules	1
10	Array Open Circuit Voltage (V_{oc})	77.18V
11	Array Short Circuit Current (I_{sc})	32.41A
12	Array Voltage at MPP (V_{mpp})	69.40V
13	Array Current at MPP (I_{mpp})	29.16A
14	Array Power at MPP (P_{mpp})	2024W



(a)



(b)

Fig. 2 V-I & P-V characteristics of GaAs cell-based PV array (a) Irradiance, and (b) Temperature.

Notably, the single GaAs solar cell can generate a maximum voltage of 0.964V extracted from solar cell efficiency tables-version 60 [5]. The open circuit voltage of the GaAs cell is 1.072V, and its efficiency is more than 29%, as proved by Atla devices [5]. GaAs solar cells outperform all other single-junction semiconductor materials like germanium, monocrystalline silicon, perovskite, and organic cells. The temperature coefficient is an essential parameter in the context of solar Photovoltaic (PV) materials and their efficiency.

It represents the percentage change in the efficiency of a solar cell for each degree Celsius change in temperature from a standard reference temperature, which is often 25 degrees Celsius. Solar cells such as Silicon (Si) and germanium are typically experiencing a decrease in efficiency as the temperature increases. It is essential to mention that GaAs are not entirely resistant to all environmental factors [19]. The detailed electrical behaviour of GaAs solar cell constructed 2KW PV array is observed for different temperatures and irradiances, which are shown in Figure 2.

2.2. Depiction of Optimum DC-DC Boost Converter

Ripple in load side parameters, slow response for dynamics in climate changes and change in load current are the major challenging issues in the design of voltage-based DC-DC converters for a PV system. The DC-DC boost converter is the most critical component in renewable energy systems, which steps up the low input voltage level into the desired higher voltage level.

The optimum DC-DC boost converter is used by considering the unpredictable meteorological conditions and reducing the output ripples by employing an inductor and capacitance-based filter [6]. Input capacitance (C_{IN}), output capacitance (C_O) and inductance (L) are shown in Equations (3), (4), & (5),

$$C_{IN} = \frac{4V_{mpp}(STC)D_{mpp}(STC)}{\Delta V_{IN}(STC)R_T(STC)f_s} = 2.83e-3F \quad (3)$$

$$C_O = \frac{2V_O(STC)D_{mpp}(STC)}{\Delta V_O(STC)R_O f_s} = 3.49e-5F \quad (4)$$

$$L = \frac{V_{mpp}(worst)D_{mpp}(worst)}{2\Delta I_O(worst)f_s} = 1.12mH \quad (5)$$

The values of input and output capacitances are calculated by using STC parameter values. Similarly, the inductor value was calculated using worst-condition parameter values [6].

2.3. P&O Method

This algorithm is defined from the perturbation of the system by the increase/decrease in reference PV array voltage acting directly on the Duty cycle of the boost converter, then observing the effect of the output power of the PV panel [8]. Then, the present value of the power P(k) panel is greater than the previous value P(k-1). Then, it retains the same direction of the previous disturbance, or we reverse the disruption of the previous cycle, as shown in Figure 3.

2.4. Fuzzy Logic Method

The fuzzy logic system uses linguistic variables instead of numerical values, and it is the most active tool in the research area. Compared to other conventional techniques, FLC provides solutions for complex indefinite difficulties which human operators can control without any mathematical calculations [9]. A fuzzy logic controller has two inputs, namely, error e(k) and changes in error Δe(k), and it is given by,

$$e(k) = (V_{ref} - V_k)$$

$$\Delta e(k) = e(k) - e(k-1)$$

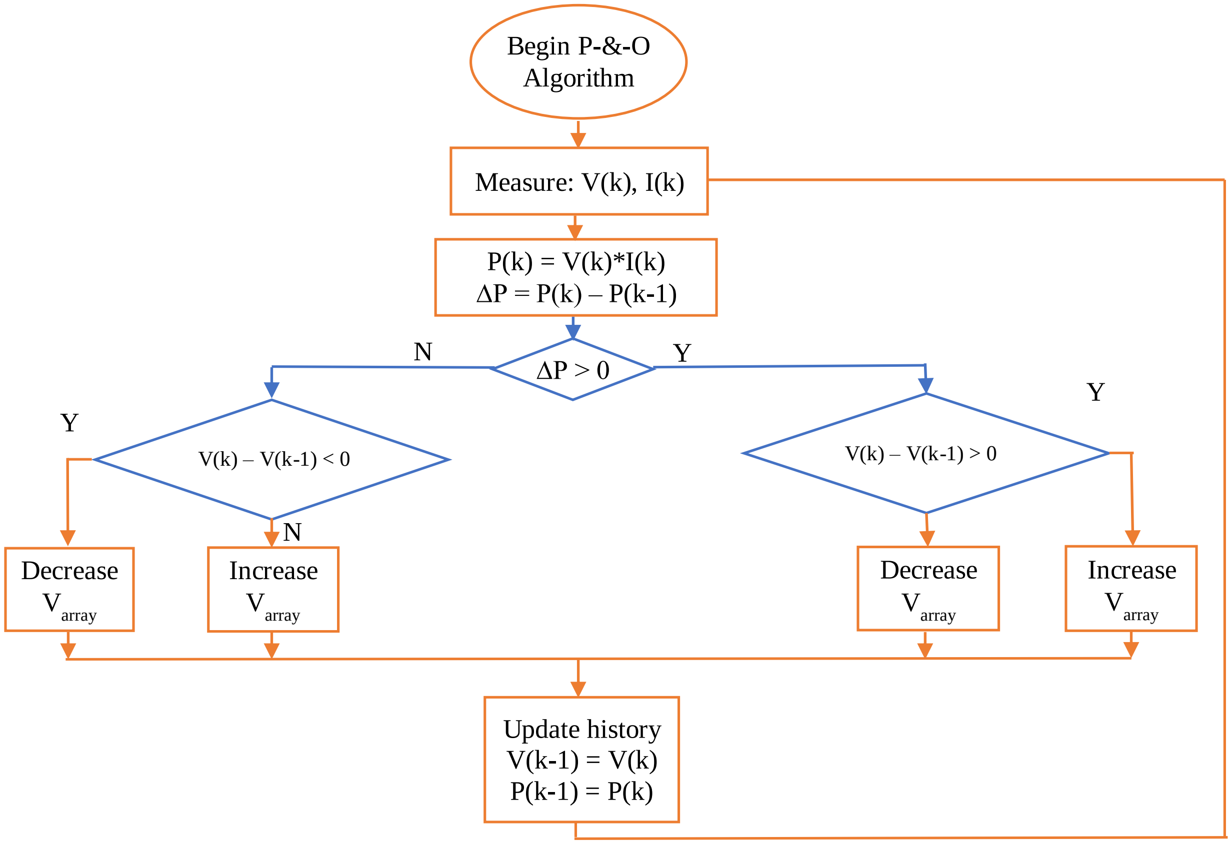


Fig. 3 Flowchart for P&O algorithm

The first step in the FLC design is to define the membership functions for the input values. In this paper, seven fuzzy levels are defined by the following fuzzy set values for error, change in error and output values, as shown in Figures 4, 5, & 6, respectively. The higher number of fuzzy levels increases the input resolution, and triangular membership functions are used in this work because of their simplicity [10]. The heuristic control rules align the fuzzy output with the fuzzy inputs, which are derived through an inspection of the system's behaviour. The FLC utilizes the rule table given in Table 2. In this study, meticulous consideration is given to the selection of the solar cell for its elevated efficiency.

At the same time, the choice of the DC-DC converter is based on its ability to perform optimally under both favourable and adverse climate conditions. Subsequently, the subsequent section focuses on the implementation of the Support Vector Regression (SVR) algorithm to enhance the overall performance of the PV system.

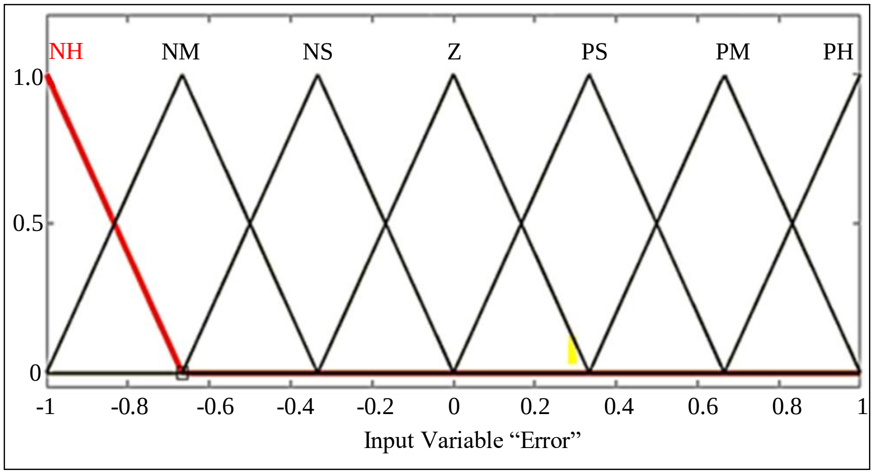


Fig. 4 Error membership function

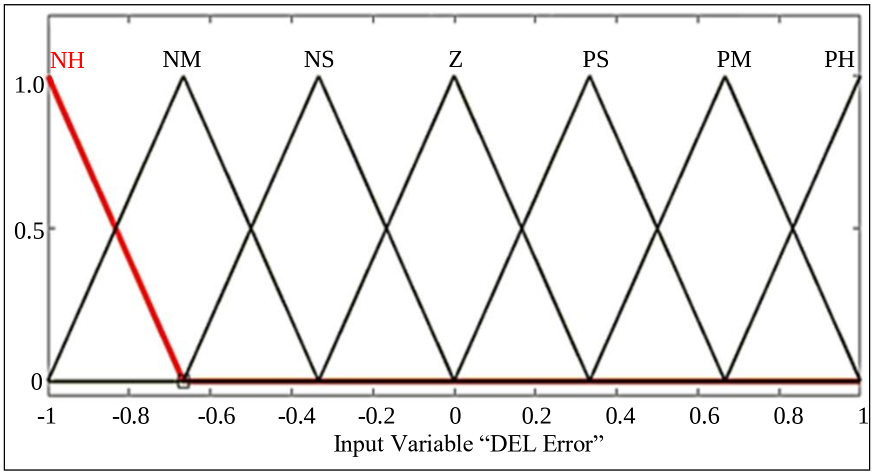


Fig. 5 Change in the error membership function

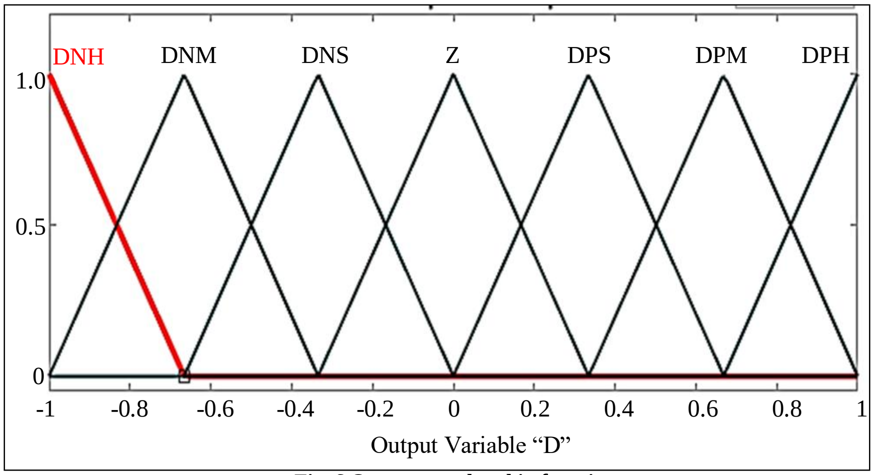


Fig. 6 Output membership function

Table 2. Fuzzy truth table

Variable	NH	NM	NS	Z	PS	PM	PH
PH	Z	PS	PM	PH	PH	PH	PH
PM	NS	Z	PS	PM	PH	PH	PH
PS	NM	NS	Z	PS	PM	PH	PH
Z	NH	NM	NS	Z	PS	PM	PM
NS	NH	NH	NM	NS	Z	PS	PM
NM	NH	NH	NH	NM	NS	Z	PS
NH	NH	NH	NH	NH	NM	NS	Z

2.5. Overview of SVR Model

The SVR algorithm forms the foundation of the MPPT controller in the PV system. SVR is a machine learning technique used to predict continuous output values, making it suitable for optimizing the PV system's power output [16]. SVR proves valuable when provoked with intricate connections between input parameters and output results, especially in situations marked by non-linear relationships. Its objective is to expose a function that effectively translates input features into continuous output values, all the while minimizing prediction errors within a specified range.

SVR operates by identifying a hyperplane within a complex and high-dimensional feature space that optimally aligns with the training data. SVR goes beyond mere error reduction, which introduces a tolerance tube around the hyperplane and allows for a permissible level of error within this spatial constraint.

The potential applications of SVR in MPPT lie in its capability to handle complex and non-linear relationships between input constraints (such as solar irradiance temperature) and the corresponding power output of a photovoltaic system. Traditional MPPT methods often rely on simplified models or heuristics that might not capture the intricate relationships between various parameters accurately. SVR-based MPPT algorithm can capture these complex relationships and provide more accurate forecasts of power output.

By training an SVR model with predicted data that includes various environmental conditions, the SVR algorithm-based MPPT controller can predict the power output based on real-time measurements of input parameters. This prediction can manage the adjustment of the system's operating point to maximize power point in any situation with rapidly changing conditions, shading, or partial cloud cover. The SVR basic equation is formed with a training dataset with the input variable as 'X' and the response as 'y'. The assignment of SVR is to discover the regression function f(x), which predicts the y values continuously based on the input dataset X. The basic SVR equation is given in Equation (6).

$$f(x) = \sum_{i=1} N\alpha_i K(x, x_i) + b \tag{6}$$

Where, N represents the count of training instances in the dataset, ∝i are the Lagrange multipliers associated with each training sample, xi is the input features of the training samples, K (x, x_i) is the kernel function that computes the similarity between the input features x and the training sample xi in a transformed space and b is the bias term.

The Lagrange multipliers ∝i are found by solving the dual optimization problem that involves maximizing a dual objective function subject to certain constraints, typically based on the margin and the epsilon-insensitive loss [17]. The selection of the kernel function is denoted as K (x, xi), is contingent upon the nature of the problem at hand and may include options such as linear, polynomial, radial basis function, and sigmoid, among others. The kernel function is used to implicitly transform the input features into a higher-dimensional space, allowing SVR to capture complex relationships between features and target values.

3. Methodology

There are three steps involved in this proposal of work. The higher efficiency GaAs solar cell is utilized for constructing the two-kilowatt solar array, carefully designed (considering best and worst irradiance and temperature) DC-DC boost converter is used to transform the PV power (P_{PV}) to load power (P_{OUT}), and finally, the ML-based SVR MPPT algorithm is applied to track the power at MPP always closer to predicted values. The P_{MPP} always depends on the irradiance (I_G) and real temperature (T_r), and so the SVR uses IG and Tr as input features 'X' to guess the Voltage at Maximum Power Point (V_{MPP}) Current at Maximum Power Point (I_{MPP}). The predicted values of V_{MPP} and I_{MPP} are used to calculate reflected input resistance (R_T), which is identical to Resistance at MPP (R_{MPP})at an optimized value of the DC-DC converter's Duty cycle (D).

3.1. Data Collection and Pre-Processing

Data collection involves gathering information about the photovoltaic system's performance under various environmental conditions. This data serves as the training, testing and justification dataset for the SVR algorithm. The parameters to be collected for training and testing are irradiance, temperature, PV voltage & current. Raw data collected from the PV system may contain noise, outliers, and irregularities that can affect the SVR model's performance. Pre-processing steps are necessary to enhance data quality and model accuracy. They are data cleaning, feature selection, feature scaling, data scaling and data augmentation.

3.2. Selection of ML Tool and Input Features

The solar panel parameters (I_G, T_r, V_{MPP} & I_{MPP}) are utilized to train, test and validate the proposed model. MATLAB/SIMULINK platform is used to develop the SVR model to be implemented for MPPT control of the PV system.

3.3. Kernal Selection and Model Training

Support Vector Regression is a predictive modelling algorithm that aims to find a function that best represents the relationship between input features and continuous output values. Unlike traditional regression, SVR focuses on minimalizing the prediction error while allowing a certain margin of tolerance. The critical components of SVR are the Kernal function, support vectors, Epsilon-tube and regularization Constant (C).

The steps to implement the SVR algorithm for MPPT control in the PV system are data preparation, Kernal selection, feature scaling, parameter tuning, model training, prediction and MPPT adjustment. Kernal selection depends on the characteristics of the dataset selected for the particular application. The standard kernels are linear, polynomial and Radial Bias Function (RBF). Train the selected SVR model using a training data set that finds a best-fit data function to minimize the deviation.

3.4. Hyperparameters Tuning and Model Evaluation

Hyperparameter tuning is done to optimize the performance of the trained SVR model by adjusting the C, Epsilon and RBF kernels. Random search or grid search methods are the methods available for this optimization. Random search is adopted in this work because it tries with all possibilities of combination. After training, the SVR model is evaluated using a cross-validation method, which generalizes the model to obtain unseen data.

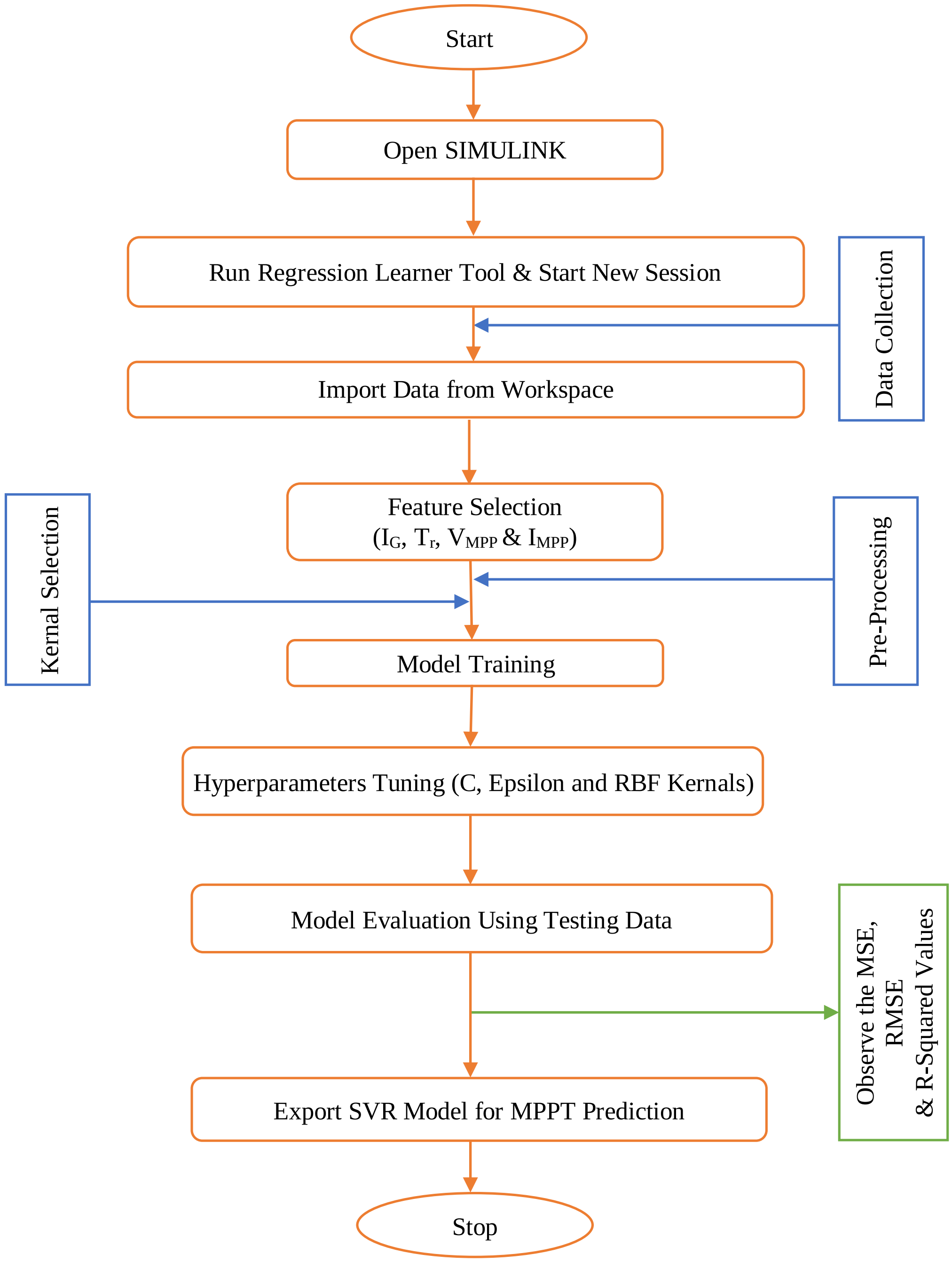


Fig. 7 Workflow of proposed SVR algorithm

The trained SVR model provides crucial factors to assess its performance using appropriate metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R-squared.

These metrics quantify the accuracy and reliability of the SVR predictions and their effectiveness as an MPPT controller. In this work, the SVR algorithm is implemented as the core of the MPPT controller; the PV system can intelligently adjust its operating point to track the MPP, enhancing overall energy efficiency and system performance. The detailed workflow of the proposed SVR algorithm is shown in Figure 7.

3.5. MPPT Control Parameters

The Duty cycle is the key parameter to operate the DC-DC boost converter closer to the maximum power point. This Duty cycle value is decided by R_T and load resistance (R_L).

$$R_T = R_L(1 - D)^2 \tag{7}$$

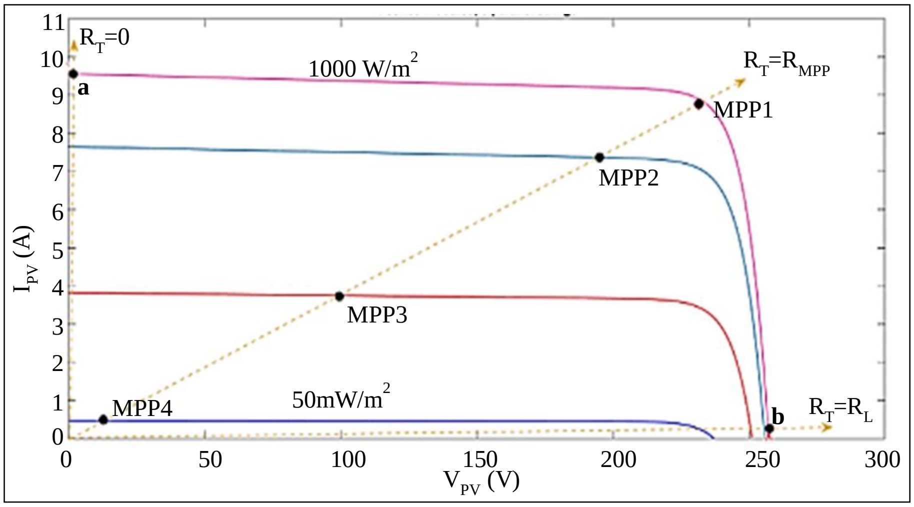


Fig. 8 MPPT using R_T for various irradiances

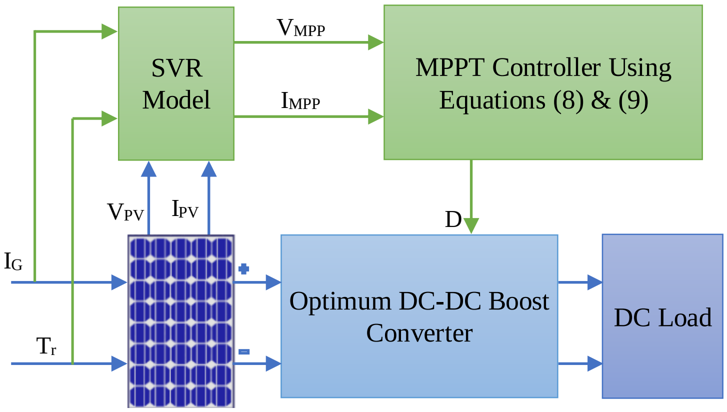


Fig. 9 Block diagram of proposed SVR MPPT-based PV system

Apply D=1 in Equation (7), $R_T = R_L(1-1)^2 = 0$. Now, the reflected input resistance (R_T) is approximately lying along the y-axis at point 'a', as shown in Figure 8, which means that the MPP is approximately closer to the short circuit operating point [6].

Similarly, apply D = 0. In Equation (7), we get $R_T = R_L(1-0)^2 = R_L$. Now, the reflected input resistance (R_T) is approximately lying along the x-axis at point 'b', as shown in Figure 8, which means that the MPP is approximately closer to the open circuit operating point. The reflected input resistance can lie in any region across the two extreme points (D = 1 and 0), as shown in Figure 8. The reflected input resistance (R_T) at MPP and Duty cycle at maximum power point (D_{MPP}) is calculated as shown in Equations (8), and (9). The value of R_T is calculated by using the SVR-trained model output values of V_{MPP} & I_{MPP}.

$$R_T = R_{MPP} = \frac{V_{MPP}}{I_{MPP}} \tag{8}$$

$$D_{mpp} = 1 - \sqrt{\frac{R_T}{R_L}} \tag{9}$$

The graphical block diagram of the ML SVR algorithm-based MPPT controller for GaAs solar photovoltaic system using an optimum DC-DC boost converter is shown in Figure 9.

4. Simulation Results Analysis of Proposed ML SVR MPPT Model

The proposed SVR model for MPPT control is trained, tested and evaluated with two input parameters (I_G & T_r) on SRV-I and the predicted responses (V_{MPP} & I_{MPP}) on SVR-II. Cross-validation (5 folds) is adopted to protect against data overfitting during the partition of data sets in folds and estimate accuracy on each fold. The SVR model is trained using a Linear Support Vector Machine and by linear kernel function.

The training results are observed as RMSE being 0.34381, MSE being 0.11821, and R-squared being 0.99, where the technical parameters of the SVR model are automatically adjusted to obtain better training results. The true and predicted data of the proposed SVR model is shown in Figure 10. It is clear that the prediction is more accurate with less error. The presence of residual of both trained and tested data on SVR-I and SVR-II levels are shown in Figures 11, and 12. It is detected that the residuals of SVR-I (V_{MPP}) lie in the range of -0.6 to 0.6, whereas the residuals of SVR-II (I_{MPP}) lie in the range of -30 to 30. The expected voltage at the maximum power point exists with minimum residuals, as indicated in Figure 11, and it is similar to the current at MPP. The data set for (I_G, T_r, V_{MPP} & I_{MPP}) is generated by using specific MATLAB code. This data set is utilized in the training and testing of the SVR model. The PV voltage (V_{PV}) & power (P_{PV}) load voltage (V_{OUT}) & power (P_{OUT}) developed by SVR model-based MPPT control at Standard Test Conditions (STC) by using an optimized DC-DC boost converter is shown in Figure 13.

The observed responses are more accurate and stable. The mean efficiency of the proposed SVR model at STC and in dynamic climate is shown in Figure 14. Also, the mean efficiency of the PV system is disturbed during the transition of minimum irradiance (at instant 1 sec from 400 w/m^2 to 600 w/m^2). The magnitude of output power is slightly higher than the PV power because of internal converter losses.

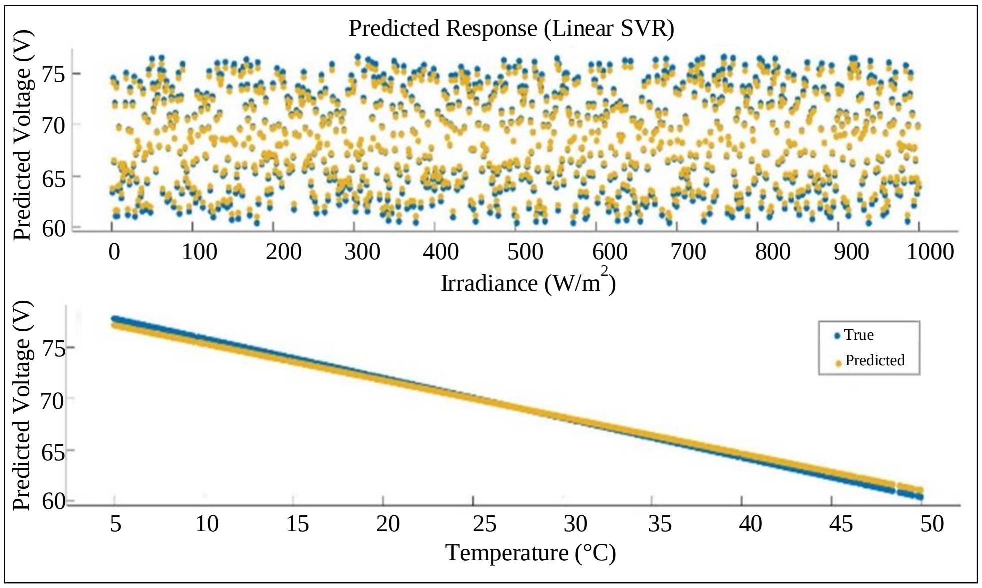


Fig. 10 True and predicted data of the proposed SVR model

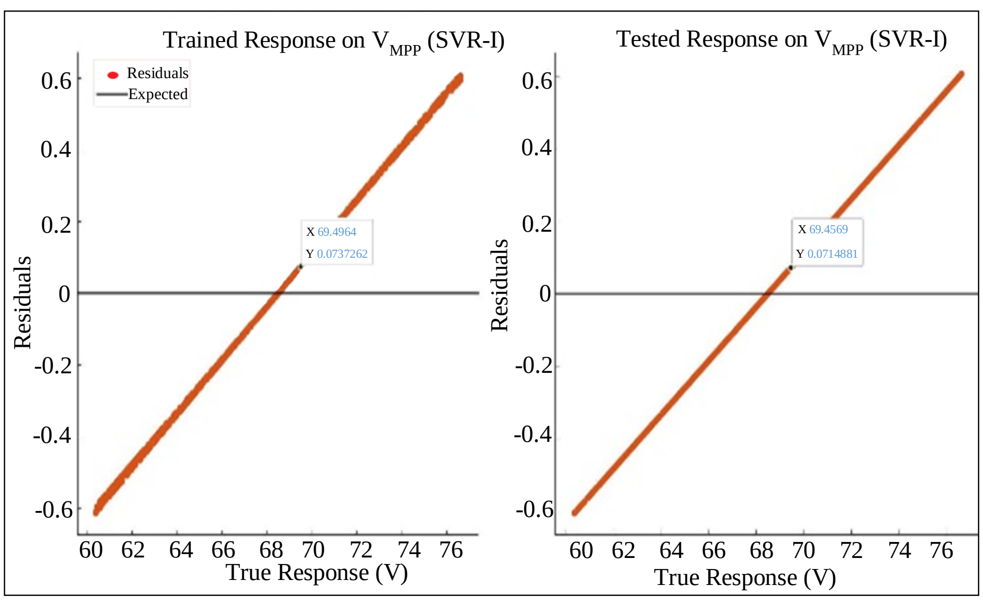


Fig. 11 Trained and tested response on SVR-I level

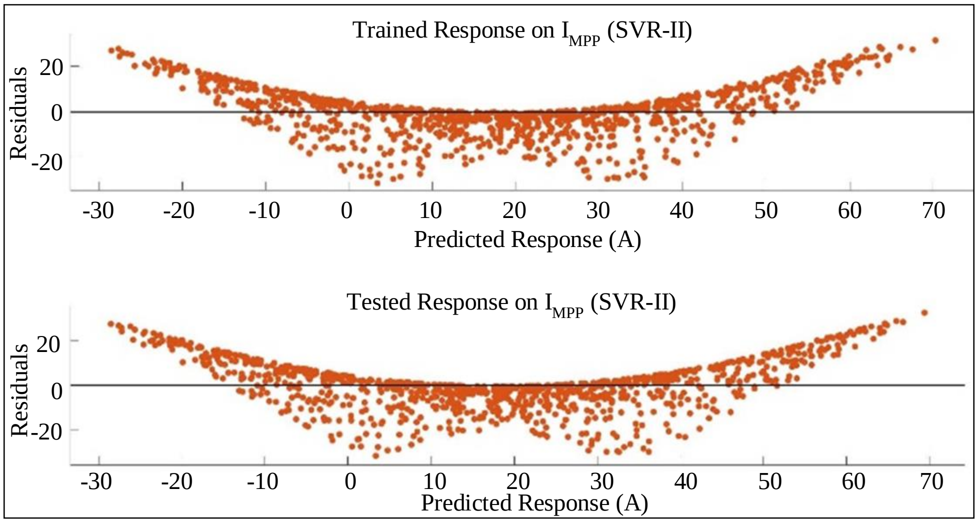


Fig. 12 Trained and tested response on SVR-II level

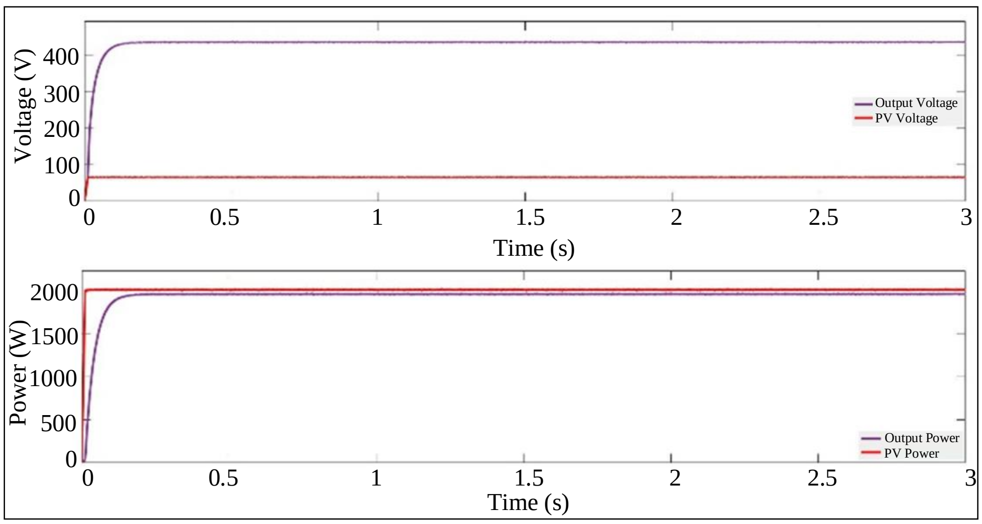


Fig. 13 PV and load (voltage & power) outcomes at STC using the SVR model

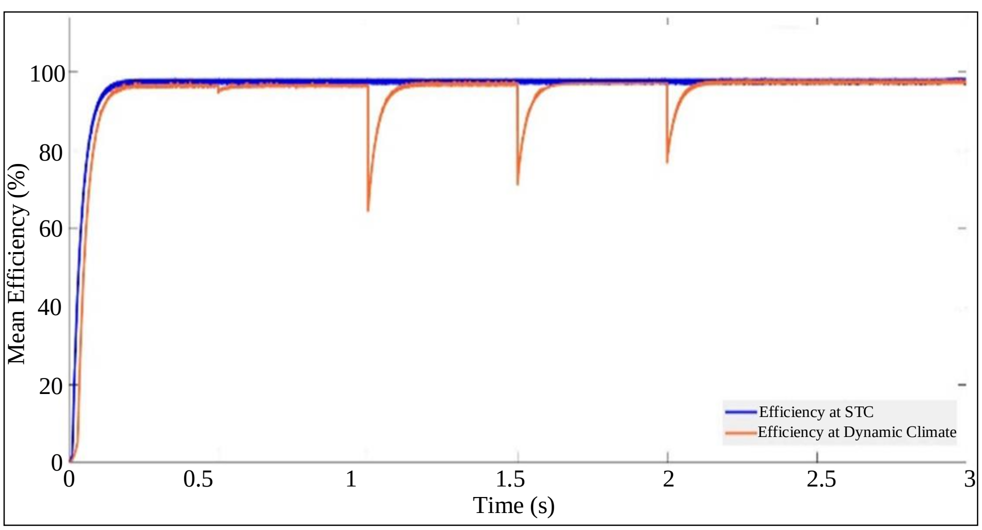


Fig. 14 Mean efficiency at STC and dynamic climate using the SVR model

To assess the effectiveness of the projected SVR model, the Photovoltaic (PV) system is subjected to dynamic climatic conditions, as detailed in Table 3, across varying time intervals. During each time segment, irradiance and temperature values are systematically randomized while maintaining other technical parameters constant. The PV voltage (V_{PV}) & power (P_{PV}) load voltage (V_{OUT}) & power (P_{OUT}) developed by SVR model based MPPT control under dynamically varying input parameters are shown in Figure 15.

The study reveals a notable observation that the VMPP remains consistently stable and accurate, irrespective of alterations in climatic conditions, distinguishing it from other MPPT controllers. The PV power exhibits a substantial rate of fluctuation in response to alterations in irradiance levels (at instants 1, 15, and 2 seconds), as depicted in Figure 15 and aligned with the data presented in Table 3. In contrast, minimal changes are observed in PV power due to variations in temperature (at an instant 0.5 seconds).

The P&O MPPT algorithm is used to control the Duty cycle for the optimum DC-DC boost controller, as discussed in section 2.3. The outcomes (PV voltage and power) of the P&O MPPT controller have been compared with the SVR model, as shown in Figure 16. It shows that there is an oscillation in both voltage and power to track the maximum point in the case of P&O MPPT control.

Table 3. Variable inputs for PV panel at different intervals

Time (sec)	I_G (W/m^2)	T_r (°C)
0 to 0.5	400	15
0.5 to 1	400	35
1 to 1.5	600	20
1.5 to 2	800	25
2 to 3	1000	25

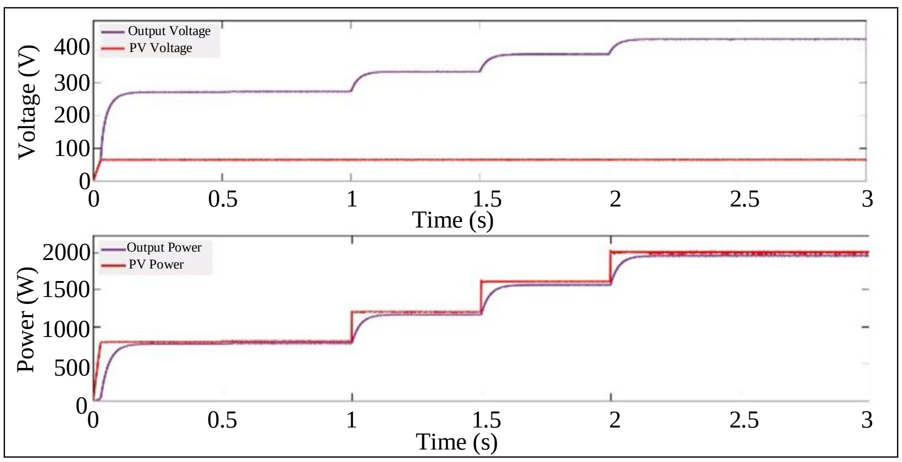


Fig. 15 PV and load (voltage & power) outcomes under dynamic climate using SVR model

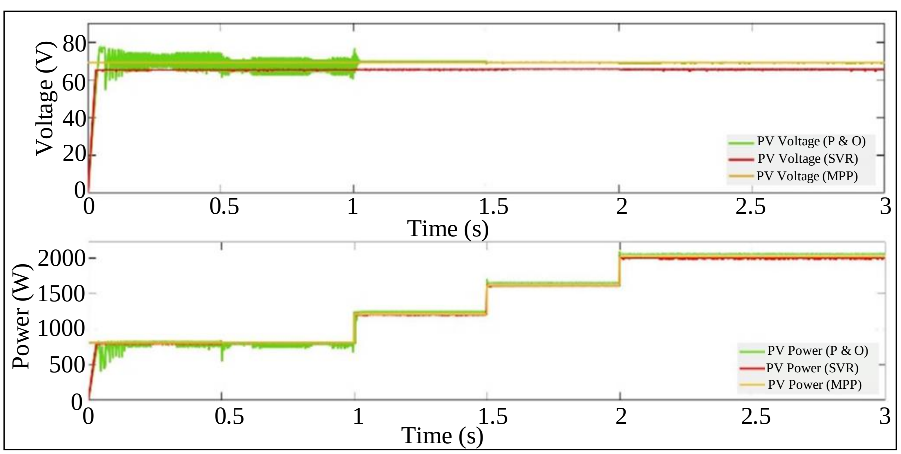


Fig. 16 PV voltage & power comparison of the SVR model with the P&O method

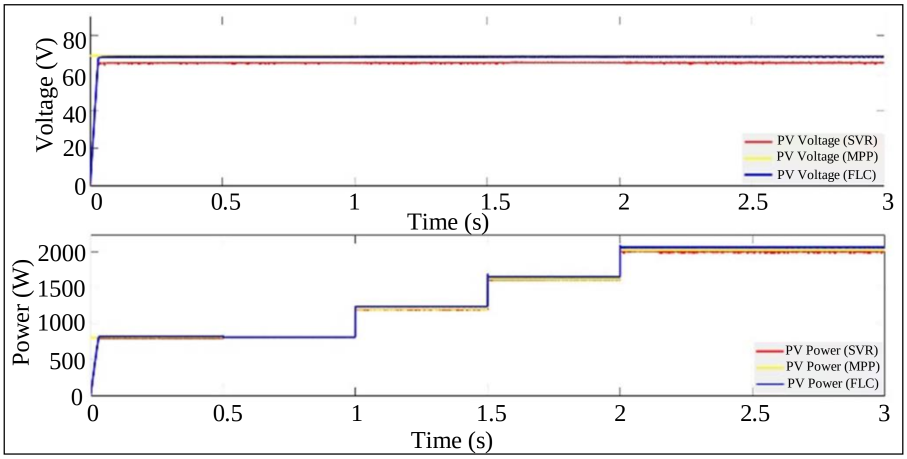


Fig. 17 PV voltage & power comparison of SVR model with FLC method

Table 4. Numerical analysis of MPPT controllers

MPPT	V_{PV} (V)	V_{OUT} (V)	P_{PV} (W)	P_{OUT} (W)	T_r (ms)	Ts (ms)	ME (%)
SVR Model	68.6	434	2021	1968	9.12	2.97	96.6
FLC	68.3	432	2018	1948	4.96	4.47	95.2
P&O	684	431	2015	1940	4.33	18.02	94.5

Fuzzy Logic Control comes from the AI family, which tracks the MPP in dynamic climates in a better manner than the existing traditional MPPT controllers. FLC is straightforward to handle, and it can effectively deal with non-linear PV systems. Its operation is based on fuzzification, fuzzy rule base, inference method and de-fuzzification, as discussed in section 2.4. The outcomes (PV voltage and power) of the FLC MPPT controller have been compared with the SVR model, as shown in Figure 17. The responses of FLC are almost similar to the SVR model based MPPT controller. However, FLC emulates human-like decision-making based on linguistic rules. It uses fuzzy sets and linguistic variables to model uncertainty and imprecision in system behaviour.

FLC generates control signals based on predefined fuzzy rules and membership functions. When dealing with SVR, the objective is to discover a model that optimally aligns with the training data, concurrently regulating the margin and minimalizing discrepancies. The MPPT technical outcomes are listed in Table 4. The SVR model achieves stable and accurate results with a high Mean Efficiency (96.6%), swift Settling Time (2.97 ms), and zero Percentage Overshoot (PO). It consistently attains the MPP, ensuring optimal energy conversion.

FLC maintains a good Mean Efficiency (95.2%) and low Percentage Overshoot (PO) while settling slightly slower (4.47 ms) compared to the SVR model. P&O exhibits a minor oscillation reflected by a low Percentage Overshoot (1.33%). However, it takes longer to settle (18.02 ms) and has a lower Mean Efficiency (94.5%). As a whole, the proposed SVR model excels in terms of efficiency, stability, and response time, making it a promising choice for enhanced photovoltaic power generation across diverse conditions.

5. Conclusion

In conclusion, this research introduces a precise and stable MPPT technique employing a Machine Learning-based SVR model, which is integrated with an optimized DC-DC boost converter for a GaAs solar-cell based PV system. The primary objective of this study is to enhance the overall efficiency of the PV system by carefully selecting the solar cell, enhanced DC-DC converter and MPPT controller. The SVR model-based MPPT controller achieves an impressive mean efficiency exceeding 96%, attesting to its stability across Standard Test Conditions (STC) and varying climatic scenarios. The comprehensive investigations and comparisons with P&O and FLC enabled MPPT methods have been conducted under both STC and dynamic climatic conditions that positively underscore the superior stability, accuracy and efficiency of the proposed SVR model. It is obvious that Machine Learning-based MPPT control strategies are poised to impact future research in renewable energy significantly and hold substantial promise within the global photovoltaic market.

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