

Optimization of PV Systems Using Data Mining and Regression Learner MPPT Techniques

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ABSTRACT

Supervised machine learning techniques such as artificial neural network (ANN) and ANFIS are powerful tools used to track the maximum power point (MPPT) in photovoltaic systems. However, these offline MPPT techniques still require large and accurate training data sets for successful tracking. This paper presents an innovative use of rational quadratic gaussian process regression (RQGPR) technique to generate the large and very accurate training data required for MPPT task. To confirm the effectiveness of the RQGPR technique, the combination of ANN and RQGPR as ANN-RQGPR technique results were compared with the conventional ANN technique results, and that of combined ANN and linear support vector machine regression as ANN-LSVM technique results under different weather conditions. Results show that ANN-RQGPR technique produced the overall best result and with an improved performance.

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1. INTRODUCTION

Photovoltaic (PV) solar energy is a category of sustainable energy that generates its energy naturally from sunlight. This form of energy is the dominant type of renewable energy source as PV energy is considered to be less pollutive, inexhaustible, noise free, and readily available compared to the fossil fuel energy [1]. The PV cells convert light energy into electrical or heat energy. However, these PV cells usually produce low and abnormal power when used without a working maximum power point tracking (MPPT) controller [2]. In stand-alone PV systems, MPPT controllers are used to enhance the flow of power from the connected PV cells to the connected load. In battery-connected PV systems, MPPT techniques are used to protect batteries from over-charging and deep discharge of power from the cells [3]. Also, MPPT techniques can increase the efficiency of PV cells during cold temperature and cloudy days when the sun irradiance is low [4]. MPPT techniques are classified into three categories: online, offline, and hybrid MPPT techniques [5]-[10].

Recent research has adopted the use of global optimization techniques such as genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), ant bee colony (ABC) and improved conventional MPPT techniques such as modified Perturb&Observe and modified incremental conductance to improve the tracking efficiency of MPPT controllers in PV systems [5], [11]. Nevertheless, few work is done using data mining techniques to track the maximum power point in PV systems. Data mining is a computing and statistical tool used to discover patterns, remove noise, extract information from large data sets, and conversion of filtered data sets into a logical structure for further use. Data mining combines machine learning, statistics, and database systems into an all-in-one technique. Tasks solved using data mining techniques are broadly divided into six categories: cluster analysis, anomaly detection, classification,

summarization, regression, and association rule learning (dependency modelling) [12]. Cluster analysis is used to learn the similarities that exist in data sets. Anomaly detection detects the error in data sets. Classification simplifies the known structure in new data sets. Summarization offers an extra compact representation of the data sets while regression learning estimates the relationship with data sets and attempts to find a function that models the data sets with least error. Regression learning uses predictive analysis to obtain more accurate results from a decision support system. Dependency modelling examines the relationships with variables [13].

The contribution of this paper is to introduce the use of a particular class of data mining techniques known as regression learning algorithm for optimization and improvement of MPPT controllers in PV systems. The regression learning algorithms considered are linear support vector machine (LSVM) regression technique and rational quadratic gaussian process regression (RQGPR) technique. These regression algorithms use few real-time samples to generate the new data sets needed to train the ANN for MPPT task. Second contribution is a work done to evaluate the feasibility of the two proposed regression learning algorithms (LSVM and RQGPR) that were combined separately with ANN as ANN-LSVM and ANN-RQGPR technique respectively for the enhancement of MPPT techniques in PV systems under different weather conditions.

The synopsis of this paper is prepared as follows, section 2 will present a summary of the used MPPT techniques. In section 3, a report of the experiment setup and method is provided. Section 4 will present the results, and section 5 will include the conclusions.

2. MPPT TECHNIQUES

The techniques used in this study are briefly discussed:

2.1. Linear-Support Vector Machine (LSVM)

Support vector machine (SVM) is a popular machine learning technique used for classification and regression analysis. SVM regression technique was first introduced by Vladimir Vapnik in 1992 and has been widely used to solve pattern recognition problems, particle identification problems, and optimization problems [5]. Examples of SVM regression techniques include the fine SVM, medium SVM, coarse-gaussian SVM, and linear support vector machine (LSVM) regression technique [13]. The LSVM regression technique aims at finding a linear function $f(x)$ with the minimal norm value ($\beta'\beta$) that makes the function $f(x)$ to be as flat as possible using what is called primal formula and dual formula. The primal formula is briefly described using Equations (1-2), while Equations (3-6) illustrate the working principle for the dual formula used in linear SVM regression analysis,

$$f(x) = x'\beta + b \tag{1}$$

$$J(\beta) = \frac{1}{2}\beta'\beta + C\sum_{n=1}^N(\epsilon_n + \epsilon_n^*) \tag{2}$$

$$L(\alpha) = \frac{1}{2}\sum_{i=1}^N\sum_{j=1}^N(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)X_i'X_j + V \tag{3}$$

$$V = \epsilon\sum_{i=1}^N(\alpha_i + \alpha_i^*) + \sum_{i=1}^N y_i(\alpha_i^* - \alpha_i) \tag{4}$$

$$\beta = \sum_{n=1}^N(\alpha_n - \alpha_n^*)x_n \tag{5}$$

$$f(x) = \sum_{n=1}^N(\alpha_n - \alpha_n^*)(x_n'x) + b \tag{6}$$

Where x_n are the data sets comprising of N observations, y_n is the response, ϵ_n and ϵ_n^* denote the slack variables for each point, while α_n and α_n^* are non-negative multipliers for each observation x_n [14].

2.2. Rational Quadratic-Gaussian Process Regression

Rational quadratic gaussian process regression (RQGPR) is a type of gaussian process regression (GPR) technique that uses rational quadratic kernel (covariance) in solving optimization, regression, training and prediction problems [15]. The regression kernel helps to determine the characteristics (e.g. fitness, smoothness, periodicity, etc.) of a function $f(x)$. The RQGPR kernel is denoted using Equation (7). The RQGPR technique exhibits some similarities with the squared exponential GPR when the scale mixture parameter (σ) from Equation (7) approaches zero [16]. The above-mentioned square exponential GPR kernel can be represented using Equation (8),

$$K_{rq}(x, x') = \sigma^2 \left[1 + \frac{(x - x')^2}{2\sigma l^2} \right]^{-\sigma} \quad (7)$$

$$K_{se}(x, x') = \sigma^2 \cdot \exp\left[-\frac{(x - x')^2}{2l^2}\right]^{-\sigma} \quad (8)$$

Where $K(x, x')$ is the covariance kernel, variable x and x' are the input variables, σ^2 is the maximum covariance, and l is the scaled-length used to determine how quickly a GPR varies with the input variable (x). Other examples of GPR kernels include matern s/2 kernel, and exponential GPR kernel [17]-[18].

2.3. Artificial Neural Network (ANN)

ANN is a machine learning technique that works like the human brain and is used to solve both linear and non-linear tasks. ANN comprises of three layers; the input layer, hidden layer, and the output layer [19]. The input layer receives the information (training data), processes the data through learning, and gives out predicted output data through the output layer. The hidden layer is an invisible layer with its output interconnected to the inputs of some other neurons [20]. In photovoltaic systems, ANN input variables can be the irradiance (G), temperature (T), open circuit voltage (V_{oc}) while the ANN predicted response can be duty cycle (D), predicted current, predicted voltage, or predicted PV power. The ANN neurons process, evaluate the input signal using linear method, then compare with its sum by means of a non-linear function known as activation function, and sends the consequence to other neurons. ANN has two common types, the feed-forward neural network and the recurrent neural network [21]. A neuron is modelled using equation (9),

$$Z = \sum_{m=1}^M X_m W_m + \alpha \quad (9)$$

where the input variables are denoted by $X_1, X_2, X_3, \dots, X_m$ and the respective weight of the individual inputs are denoted by $W_1, W_2, W_3, \dots, W_m$ respectively [5], [22]. Mathematically, the neurons in the hidden layer can be estimated using equation (10),

$$N_h = \frac{(N_i + N_o)}{2} + \sqrt{N_e} \quad (10)$$

where N_h is the hidden layer, N_i is the input layer, and N_o is the output layer. Some drawbacks with ANN technique include longer processing time for large networks, complexity of the ANN algorithm, and ANN procedure demands that the system is first trained using prior data sets and the collection of these training data sets might be cumbersome [23]-[25].

3. SIMULATION MODEL

To investigate the feasibility with the use of regression learning algorithms in tracking the maximum power point in a stand-alone photovoltaic system, an experiment was conducted using a complete photovoltaic system that includes a soltech 1STH-215-P PV panel, modified cuk DC-DC converter, MPPT controller, and a 20 Ω resistive load. The training data sets were collected from PSIM software. Table 1 illustrates the specifications of the used PV panel and the DC-DC converter in this study. The PV efficiency, load efficiency, and DC-DC converter loss were obtained using Equations (11-13),

$$PV \text{ efficiency at MPPT} = \frac{\int_0^t P_{pv(max)t} \cdot dt}{\int_0^t PV_{pv(mppt)t} \cdot dt} \tag{11}$$

$$MCUK \text{ load efficiency at MPPT} = \frac{\int_0^t P_{out(mppt)t} \cdot dt}{\int_0^t PV_{pv(mppt)t} \cdot dt} \tag{12}$$

$$MCUK \text{ Losses} = \text{input power} - \text{output power} \tag{13}$$

Where $P_{pv(mppt)}$ is the 1STH-215-P rated power at STC (standard test condition), $P_{pv(max)}$ is the PV extracted power, and P_{out} is the output power at the 20 Ω resistive.

Table 1. The Used PV Panel and MCUK DC-DC Converter Specifications

Solar Panel Specifications		Mcuk Specifications	
PV Model	1STH-215-P	L ₁	4 mH
Standard Test Condition	1000W/m ² , 25°C	L ₂	4 mH
Maximum Voltage (V _{mo})	29.0V	C ₁	100 μF
Maximum current (I _{mp})	7.35A	C ₂	100 μF
Maximum Power (P _{mp})	213.15W	R ₀	20 Ω
N _s - number of cell in series	60	C ₀	270 μF
I _{sc} - short circuit current	7.84A		
V _{oc} - open circuit voltage	36.30V		
Temp. coefficient of I _{sc}	-0.36099% / °C		
Temp. coefficient of V _{oc}	0.102% / °C		
A-Diode ideality factor	0.98117		

Figure 1 presents the flowchart algorithm of the linear support vector machine (LSVM) regression technique. The LSVM modelling was done in three folds. The first fold dealt with the optimization and generation of a fitness function (yfit) using LSVM regression kernel and few collected samples of the PSIM data sets (19 instances) in training the model. The data sets comprise of two input variables (different levels of irradiance(G) and temperature (T)) as predictors (X) and one output variable (reference current (Iref*)) as the response. The LSVM regression kernel was then used to predict the responses (Iref) for an additional 110 instances comprising of variables G and T. The second fold dealt with the training, testing, and validation of the LSVM newly predicted data sets using ANN technique. The LSVM generated data sets were split in the proportion 75% for training, 15% testing, and 15% validation.

For the third fold, Figure 2 displays a complete stand-alone PV system designed using ANN-LSVM technique. The ANN-LSVM output (reference current (Iref*)) was compared with the PV current (I_{pv}) as error signal (Iref* – I_{pv}). The error signal was passed through a power-integral (PI) controller for fine tuning and outputs the duty cycle signal (D). The duty cycle signal was transmitted through a pulse width modulator (PWM) as pulse signal that was used to activate the Mosfet gate of the DC-DC converter. Table 2 displays the average testing error of the trained ANN-LSVM MPPT technique using a total of 129 samples that comprise of 10 samples from the PSIM data sets and 119 samples from the generated ANN-LSVM data sets in the proportion 70% training, 15% testing, and 15% validation.

For the rational quadratic gaussian process regression (RQGPR) technique, similar procedures as shown in Figure 1, and a block diagram as shown in Figure 2 of a complete PV system but using RQGPR algorithm and ANN-RQGPR MPPT technique were used. Table 3 presents the ANN-RQGPR training, testing, and validation statistics. Where a value of R that is approaching 1.00000 and a MSE approaching 0.00000 validate a well trained model.

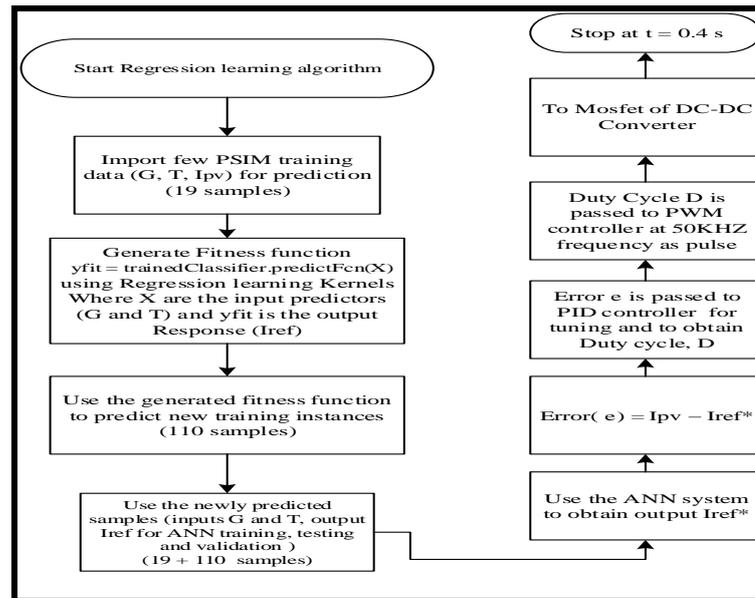


Figure 1. The ANN-LSVM algorithm

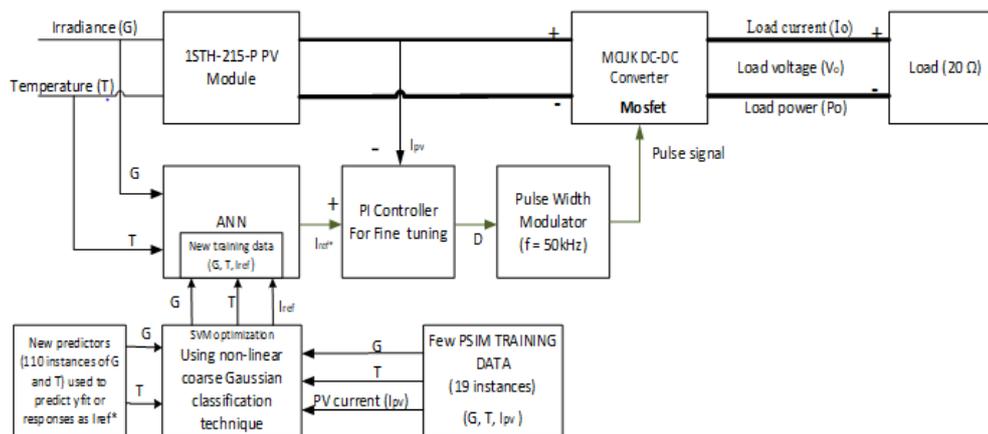


Figure 2. Complete PV system designed using ANN-LSVM MPPT technique

Table 2. The Regression (R) and Mean Square Error (MSE) Statistics for ANN-LSVM Technique

ANN-LSVM	Samples	MSE	Regression (R)
Training	91	1.94247e-9	9.99999e-1
Testing	19	1.26600e-8	9.99999e-1
Validation	19	6.20523e-7	9.99999e-1

Table 3. ANN-RQGPR Regression (R) and Mean Square Error (MSE) Statistics

ANN-RQGPR	Samples	MSE	Regression (R)
Training	91	1.28482e-9	9.99999e-1
Testing	19	5.33080e-9	9.99999e-1
Validation	19	1.79494e-7	9.99999e-1

For the conventional ANN technique, Figure 3 shows the complete PV system designed using a conventional ANN MPPT technique. Unlike the ANN-LSVM and ANN-RQGPR techniques that were trained using optimized data sets from the regression learning predictions, the conventional ANN algorithm

was trained using real data sets (129 instances of G , T , and I_{ref}) that were collected entirely from the PSIM software through a dynamic PV simulation. Table 4 displays the error statistics for the conventional ANN training, testing, and validation.

Table 4. ANN Regression (R) and Mean Square Error (MSE) Statistics

Conventional ANN	Samples	MSE	Regression (R)
Training	91	1.06304e-5	9.99998e-1
Testing	19	1.05663e-5	9.99993e-1
Validation	19	7.10019e-5	9.99990e-1

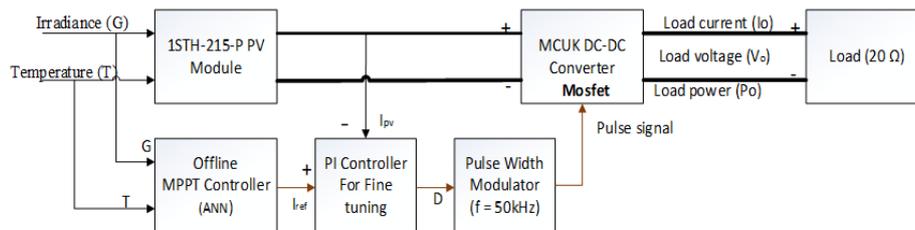


Figure 3. Complete PV system designed using conventional ANN technique

4. RESULTS AND ANALYSIS

Table 5 and Figures 4-9 present the tabulated results and the graphical results for the conducted experiment using conventional ANN technique, non-conventional ANN-LSVM and non-conventional ANN-RQGPR MPPT technique under three different weather conditions (NOCT, PTC, and STC). The NOCT is the normal operating cell temperature where the irradiance (G) is 800 W/m² and the ambient temperature (T) is 47.40 °C. STC is the standard test condition where G is 1000 W/m² and T is 25 °C while PTC is the PVUSA test condition where G is 1000 W/m² and T is 20 °C

For case 1 (NOCT), where G is 800 Wm⁻² and T is 47.40 °C, obtained results show that the conventional ANN and the non-conventional ANN-RQGPR technique had tie (same) and best results at both the PV end and at the 20 Ω resistive-load end (73.09% PV efficiency and 69.79% output load efficiency) while ANN-LSVM displayed the lowest performance (72.67% PV efficiency, 69.43% load efficiency). However, the ANN-LSVM exhibited the lowest DC-DC converter power loss under NOCT condition. Figures 4-5 display the graphical results of the extracted PV power and the output load power from the PV system using conventional ANN, non-conventional ANN-LSVM, ANN-RQGPR technique, and under NOCT weather condition.

For case 2 (PTC), where G is 1000 Wm⁻² and T is 20 °C, ANN-RQGPR had the best result (101.95% PV efficiency and 97.71% resistive load efficiency), while ANN-LSVM underperformed (100.40% PV efficiency and 97.71% load efficiency). Similarly, the DC-DC converter loss in power with ANN-LSVM regression technique was the lowest (8.56 W). Figures 6-7 display the graphical results of the extracted PV power and the output load power from the PV system using ANN, ANN-LSVM, ANN-RQGPR technique, and under PTC weather condition.

For case 3 (STC), where G is 1000 Wm⁻² and T is 25 °C, both ANN and ANN-RQGPR achieved close results at the PV end as equal powers and efficiencies were extracted from the PV system (212.90 W PV power and 99.88% PV efficiency) whereas the PV panel did underperform using ANN-LSVM (209.90 W PV input PV power and 98.48% PV efficiency). However, at the 20 Ω resistive end, ANN-RQGPR overperformed by extracting the maximum output power and efficiency (204.16 W resistive-load power and 95.78% load efficiency). Also, the ANN-LSVM MPPT technique underperformed as 201.45 W power was produced at the resistive load end and with a load efficiency of 94.45%. Figures 8-9 display the graphical results of the extracted PV power and the output load power from the PV system using ANN, ANN-LSVM, ANN-RQGPR technique, and under PTC weather condition.

In addition, at STC, the ANN-LSVM had the lowest DC-DC converter power loss as 8.45 W was dissipated at the DC-DC converter while power dissipated with ANN-RQGPR MPPT technique in all the three environmental condition cases (NOCT, PTC, and STC) were the highest. Also, from the analysed regression (R) and the mean-square-error (MSE) results shown in Tables 2-4, ANN-RQGPR had the best result while ANN had the worst training result.

Table 5. Results of the conducted experiment under varied weather conditions

Weather conditions	VALUES	ANN	ANN-LSVM	ANN-RQGPR
G = 800 Wm ⁻²	PV current (A)	5.800	5.715	5.802
	PV voltage (V)	26.57	27.04	26.77
	Load current (A)	-2.727	-2.720	-2.727
	Load voltage (V)	-54.55	-54.41	-54.55
T = 47.40 °C (NOCT)	PV power (W)	155.80	154.90	155.80
	Load power (W)	148.76	148.00	148.76
	DC-DC losses (W)	7.04	6.90	7.04
	PV Efficiency (%)	73.09	72.67	73.09
CASE 1	Load efficiency (%)	69.79	69.43	69.79
	PV current (A)	7.141	6.923	7.159
G = 1000 Wm ⁻²	PV voltage (V)	30.30	30.86	30.25
	Load current (A)	-3.226	-3.205	-3.227
	Load voltage (V)	-64.52	-64.10	-64.54
	PV power (W)	217.00	214.00	217.30
T = 20 °C (PTC)	Load power (W)	208.14	205.44	208.27
	DC-DC losses (W)	8.86	8.56	9.03
	PV Efficiency (%)	101.81	100.40	101.95
	Load efficiency (%)	97.65	96.38	97.71
CASE 2	PV current (A)	7.174	6.945	7.179
	PV voltage (V)	29.58	30.16	29.57
T = 25 °C (STC)	Load current (A)	-3.194	-3.174	-3.195
	Load voltage (V)	-63.89	-63.47	-63.90
	PV power (W)	212.90	209.90	212.90
	Load power (W)	204.06	201.45	204.16
CASE 3	DC-DC losses (W)	8.84	8.45	8.74
	PV Efficiency (%)	99.88	98.48	99.88
	Load efficiency (%)	95.74	94.51	95.78

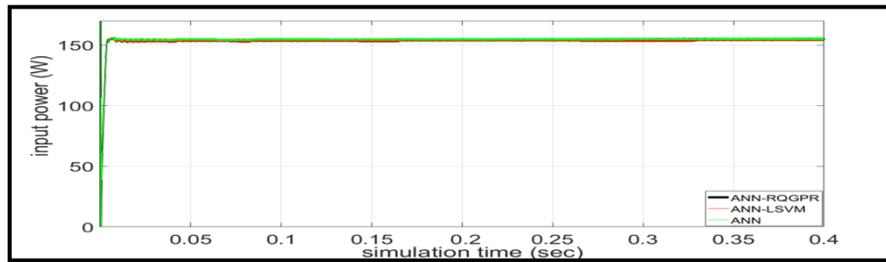


Figure 4. Graph of 1STH-215-P input power at NOCT

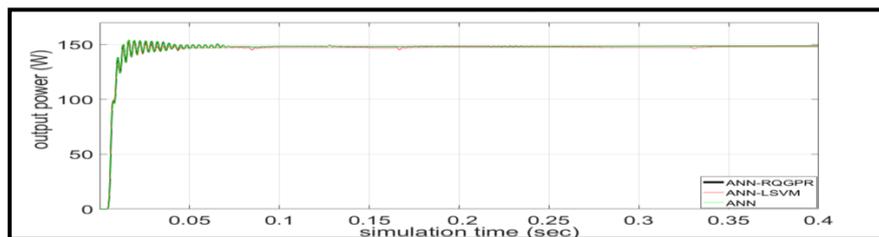


Figure 5. Graph of 1STH-215-P output power at NOCT

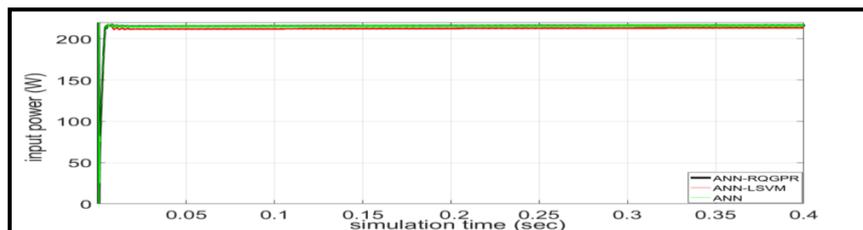


Figure 6. Graph of 1STH-215-P input power at PTC

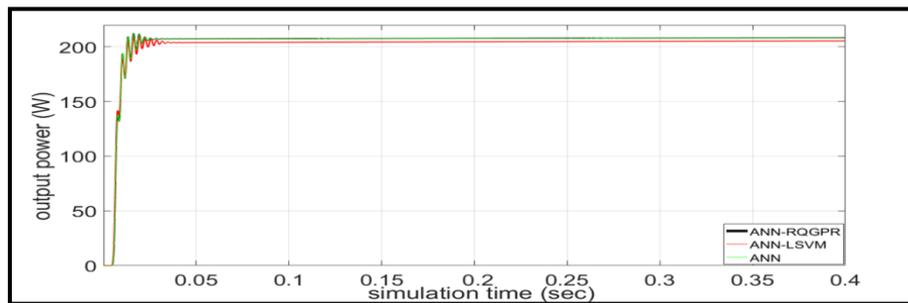


Figure 7. Graph of 1STH-215-P output power at PTC

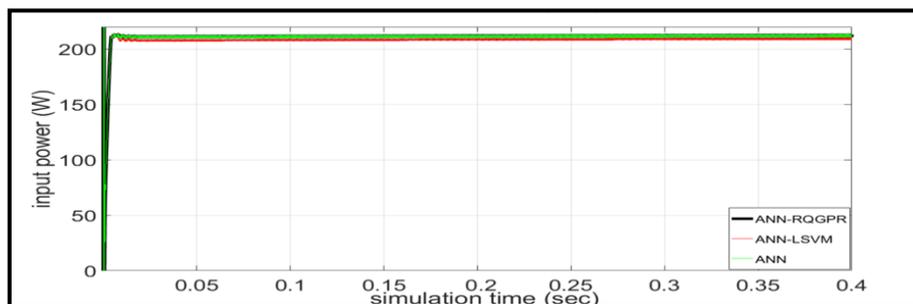


Figure 8. Graph of 1STH-215-P input power at STC

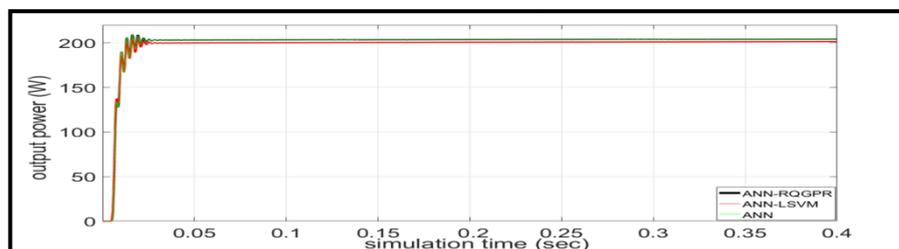


Figure 9. Graph of 1STH-215-P output power at STC

5. CONCLUSIONS

This paper presents an innovative use of a particular type of data mining technique known as the rational quadratic gaussian process regression (RQGPR) learning algorithm to track the maximum power point in PV systems. Findings suggest that optimization of PV systems using RQGPR technique can be used to extract maximum power from a photovoltaic panel under different weather conditions. The RQGPR can successfully generate the large, acceptable and accurate training data sets needed to train the supervised machine learning techniques like ANN and ANFIS for MPPT tasks. Also, the mean-square-error (MSE) and regression (R) error statistics with RQGPR technique were better than that of conventional ANN and linear support vector machine (LSVM) regression techniques. Results confirmed that RQGPR technique exhibited an improved tracking power and efficiency compared to the linear support vector machine (LSVM) regression technique.

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