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A COMPARATIVE STUDY OF SUPPORT VECTOR MACHINE AND RISK DETERMINISTIC APPROACH ON A PHOTOVOLTAIC SYSTEM

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The present paper introduces a comparative analysis of the management of a stochastic optimization problem using both a risk deterministic approach and a support vector machine strategy. This optimization problem is formulated in consideration of the influence produced by environmental factors, such as irradiance and temperature, on a photovoltaic panel. The problem will be solved by applying both methods to determine the Maximum Power Point (MPP), thereby to enhance the power generation efficiency. The primary objective is to conduct an analysis comparing the two approaches, with the aim of recommending the most suitable approach for Maximum Power Point Tracking (MPPT).

Keywords: support vector machine for regression, risk optimization, machine learning, photovoltaics

1. Introduction

The journey for efficient and robust PV systems has become a focal point in the field of renewable energy research. These systems, which convert solar irradiance directly into electricity, are at the heart of a sustainable energy future. However, the performance and reliability of PV systems are influenced by numerous factors, demanding sophisticated modeling and prediction techniques.

In the pursuit of optimizing the performance of PV panels, the management of stochastic optimization problems has become a pivotal focus of research and

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development. In this context, the present paper delves into a comparative analysis that explores two distinct methodologies: a risk deterministic approach and a support vector machine strategy. These methodologies are applied to tackle an optimization problem intricately linked to the environmental dynamics surrounding PV systems, notably irradiance.

The core objective of this comparative analysis is to discern the most effective approach for enhancing the power generation efficiency of PV panels. Central to this endeavor is the determination of the MPP, a critical parameter influencing the global performance of PV systems. These two innovative techniques will be presented in the current paper, while the other common methods used in the literature for computing the MPP were described in the case study [1].

Ultimately, the findings of this study are poised to contribute towards advancing the state-of-the-art methodologies for optimizing the performance of solar energy systems, thereby facilitating the transition towards a more sustainable and efficient energy landscape. The issues and challenges concerning the methods used for solar photovoltaic energy optimization were also addressed in [2].

Various optimization techniques have been explored to enhance the performance of MPPT algorithms, among which Support Vector Machine (SVM) optimization has emerged as a promising approach. This approach was presented for photovoltaic system monitoring in [3], together with a fault detection technique.

SVM optimization techniques offer advantages such as robustness, flexibility, and adaptability, making them suitable for optimizing MPPT algorithms for PV panels. By effectively capturing the nonlinearities and dynamics of the PV system, SVM optimization techniques enable the development of robust MPPT algorithms, capable of achieving superior performance in terms of efficiency, accuracy, and stability, as shown in [4,5].

The SVM was introduced as a supervised machine learning algorithm, which examinates data for classification and regression. Practically, based on the predictors, consisting in historical input data set, and on responses, containing previous output data set, the response for the new input data is predicted [6]. Whilst, the Risk Deterministic Approach introduce a dual deterministic problem which will be solved using mathematical techniques as it was introduced in [7]. Through this comparative study, we plan to evaluate the advantages and drawbacks of each approach in modeling and predicting the performance of PV systems. The outcomes of this research will bring relevant insights for both practitioners and researchers in the field, which supply the development of efficient and reliable PV systems.

2. Stochastic Optimization Problem

A stochastic optimization problem (SO) involves an objective function and/or constraints dependent on random variables or uncertainty. This kind of SO arises in a multitude of domains, including engineering, automotive, construction, and biomedical applications. Stochastic optimization methods are used to minimize or maximize the benefits of a statistic or mathematical function when having to deal with one or more input parameters dependent on random variables.

A standard definition of a SO is proposed in the following relation [8,9]:

$$\max\left\{J(x_n)=c^T(\omega)x_n\right\}$$
$$a.c.\begin{cases}A(\omega)x_n\le b(\omega)\\ x_n\ge 0\end{cases} \tag{1}$$

stating that J is the objective function, $c\in\mathbb{R}^{nc}$ are the coefficients of the function, x_n represents a nonlinear vector, ω is considered the random variable, $x_n\in\mathbb{R}^{nc}$ and $A\in\mathbb{R}^{nr\times nc}$ with $nr\le nc$.

Asserting that $\{A(\omega),b(\omega),c(\omega)\}$ defines a set of stochastic variables corresponding to each random variable $\omega\in\Omega$, Ω being the space of the random variables [9]. The SO in (1) is considered also nonlinear [7,8].

Taking into account all the values $x_n\in D_a$, where D_a is considered the admissible domain of the variables from (1), the relation [8,9]:

$$\max_{x_n\in D_a}\left\{J(x_n)=c^T(\omega)x_n\right\} \tag{2}$$

has lost the concept of optimization due to the fact that x_n is an aleatory variable that is not subject to the order relationship. Analogous reasoning applies to the constraints that infer the domain D_a.

Consider that for every $\omega\in\Omega$, the following problem can be solved by applying the provided constraints but transformed into egality type [8,9]:

$$\max\left\{J(x_n)=c^T(\omega)x_n\right\}$$
$$a.c.\begin{cases}A(\omega)x_n=b(\omega)\\ x_n=0\end{cases} \tag{3}$$

For the problem described in (3), the optimal solution $x_n^*(\omega)$ and $J^*(x_n(\omega))=c^T(\omega)x_n^*(\omega)$ the optimal values of the criterion function can be considered. We can conclude that $x_n^*(\omega)$ and $J^*(x_n(\omega))$ are random variables. In other words, $J^*(x_n(\omega))$ cannot be precisely computed, but it can be formulated statistically. To solve (3), two strategies can be applied: to compute the repartition function of $J^*(x_n(\omega))$ or to solve the problem by transform it into a deterministic one.

3. Risk optimization problem – Formulation

For the purpose of the current paper, the SO will be solved by redesigning the optimization in order to transform it into a deterministic risk problem.

In the current conditions, the optimization problem defined in (3) can be reformulated as a deterministic minimum risk problem [8].

$$\begin{cases} \min\{\alpha_r\} \\ \text{a.c.}: \begin{cases} P\left(c^T x_n < J_i\right) = \alpha_r \\ x \in D_a \end{cases} \end{cases} \tag{4}$$

Minimizing α_r for which $J(x) = c^T(\omega) x_n$ is lower than an imposed J_i (e.g. the average value). α_r is considered the risk of computing $J(x_n) \prec J_i$.

For the minimum risk problem defined in (4) an equivalent problem can be restated if we accept the following hypothesis:

- The vector containing random values, $c(\omega)$ follows the normal non-degenerate distribution and the μ vector of the mean values μ_i and ϑ covariance matrix of ϑ_{ij} values can be attached:

$$\begin{cases} \mu_i = E(c_i), \mu = (\mu_i) \\ \vartheta_{ij} = E\left[(c_i - \mu_i)(c_j - \mu_j)^T\right], \vartheta = (\vartheta_{ij}) \end{cases} \tag{5}$$

- The optimization problem is linear [8,9,10]:

$$J_\mu(x_n) = \max_{x_n \in D_a}\{\mu^T x_n\} \tag{6}$$

for which x_n^* is the only solution. In other words, $J_\mu(x_n)$ will attain the maximum in $J_\mu^* = \mu^T x_n^*$. Therefore, $J_i < J_\mu^*$ will be chosen.

The already described problem can be redesigned based on probabilities, considering that there is no way to compute the distribution function [8,10]:

$$\alpha_r = P\left(c^T x_n < J_i\right) = P\left(\frac{c^T x_n - \mu^T x_n}{\sqrt{x_n^T \vartheta x_n}} < \frac{J_i - \mu^T x_n}{\sqrt{x_n^T \vartheta x_n}}\right) = \phi\left(\frac{J_i - \mu^T x_n}{\sqrt{x_n^T \vartheta x_n}}\right) \tag{7}$$

, where $\phi(x_n) = \frac{1}{\sqrt{2\pi}} \int_0^{x_n} e^{-\frac{t^2}{2}} dt$ is the Laplace function defined in [8].

The simplified arising from (7) leads to a new optimization challenge, considering the monotonic increase of the Laplace function and the requirement that matrix ϑ is positively defined [8].

$$\min_{x_n \in D_a}\left\{\frac{\mu^T x_n - J_i}{\sqrt{x_n^T \vartheta x_n}}\right\} \tag{6}$$

Nonlinear programming conventional gradient approaches, that include selecting x_n^* as the best solution, can be used to address this kind of problems [8].

4. Support Vector Machine for Regression – Mathematical Model

SVM for regression (SVR) is a mathematical model that aims to acquire knowledge of a regression function that maps input predictor variables to output values. In other words, the SVR model formulates an optimization problem to identify the hyperplane that maximizes the margin among the predicted values and the real values [11]. It can be also considered a SO, if the input and output variables are influenced by random variables. The start equation for the SVM regression model can be defined as [11]:

$$y(x) = w^T x + w_0 \tag{7}$$

, where $y(x)$ symbolizes the predicted output, w is the weight vector, x express the input vector, and w_0 act as the bias coefficient. The bias term w_0 and the weight vector w are adjusted during the training process to identify the optimal hyperplane that maximizes the margin between the predicted and obtained values.

The optimization problem for SVM regression can be formulated as [12]:

$$\begin{aligned} &\min_w \frac{1}{2}\|w\|^2 + C\sum \xi_i \\ &y_i - \left(w^T x_i + w_0\right) \le \varepsilon + \xi_i \left(w^T x_i + b\right) - y_i \le \varepsilon + \xi_i \\ &\xi_i \ge 0 \end{aligned} \tag{8}$$

, where $\|w\|^2$ is the squared norm of the weight vector, C is the regularization parameter, ξ_i represents the slack variable for the i -th training sample, y_i is the actual output linked to its training sample, x_i denotes the input vector linked to the i -th training sample, and ε is the error tolerance. This problem can be computed by applying techniques similar to the quadratic programming or the convex optimization, in order to identify the optimal values for w and w_0 minimizing the objective function and in the same time satisfying the restrictions.

The kernel function matrix is used in the SVM regression model to map the input variables from their original space to a higher-dimensional feature space, allowing for non-linear regression [13,14]. And it can be defined as:

$$K = \left[\begin{pmatrix} K(x_1, x_1) & \dots & K(x_1, x_n) \\ \vdots & \ddots & \vdots \\ K(x_n, x_1) & \cdots & K(x_n, x_n) \end{pmatrix}\right] \tag{9}$$

, where $K(x_i, x_j)$ is the kernel function that computes the similarity between the i -th training sample and j -th training sample.

The final SVM regression model [12] that will be used during the training stage can be reformulated as:

$$y(x)=\sum\left(\lambda_i K(x_i,x)\right)+w_0 \tag{10}$$

, where λ_i represents the Lagrange multiplier associated with the i -th training sample, and x_i stands for the support vector.

For the current strategy, the prediction can be also evaluated based on the risk associated with the defined model, computed to reveal the variability in the SVR predictions.

Assuming that during the test stage, the $y_{test}(x)$ values are predicted, the standard deviation σ_{res} and the mean value μ_{res} associated with the residuals $res_i = y_{test}(x)-y_i$ are computed:

$$\begin{aligned} \mu_{res} &= E(res_i) \\ \sigma_{res} &= \sqrt{\frac{\sum_{i=1}^{n_{test}}\left(res_i-\mu_{res}\right)^2}{n_{test}}} \end{aligned} \tag{11}$$

The risk associated with the SVR prediction can be proposed to be calculated as:

$$r_{SVR}=\frac{\sigma_{res}}{\mu_t}\cdot 100 \tag{12}$$

where $\mu_t = E(y_t)$ and y_t will be the vector of the considered test values.

The SVR associated risk does not directly indicate whether the predictions are below or above the considered true values. Instead, it provides insight into the uncertainty associated with the model's prediction. For example, if it is high, then the predicted values may deviate substantially from the true values.

4. Case studies

4.1. Simulation definition

In this study, will be presented two distinct case studies related to photovoltaic (PV) power estimation. First, will be explored a Gaussian stochastic supervisor approach by addressing the minimum risk problem in the vicinity of the maximum point of the harvested PV power. This approach is then compared with the results of a second case study, which proposes power estimation using a Support Vector Machine (SVM) regression model. Both approaches rely on simulations based on power generation data of the PV panel established on the GECAD laboratory platform [15,16] collected with a sampling period $T_s = 5\,\min$. The GECAD system, established in Porto (Portugal) in 2012, initially featured a Kyocera KC200GH-2P 200W panel [17] integrated in a specific SMART-GRID system. For detailed technical specifications of the Kyocera panel, refer to [18].

The proposed dataset consists in 930 measurements for solar irradiance, voltage and power from 6 days in July 2013 to introduce the minimum risk optimization problem to be solved and to train SVR models. The simulations will be conducted on a system operating on Windows 11, equipped with an Intel Core i5-11300H CPU and $16GB$ of RAM.

4.2. Minimum Risk Optimization Problem approach (MROP)

Considering the characteristics of a PV panel, $P(U)$, expressing the electrical power's linkage to the generated voltage. The illustration which is grounded on real data [16,17], is visually displayed in Fig. 1. A first approach will be focused on computing a Gaussian stochastic supervisor based on addressing the minimum risk problem in the vicinity of the maximum point of the produced PV power in MATLAB R2021b.

Starting from a region as shown in Fig. 2, the interdependency $P(U)$ can be found using a quadratic interpolation polynomial. This approximation can be done by applying the direct Coggins search method [10]. In the context of this approach for the problem in (1), it was associated $J(x_n)$ representing the photovoltaic generated power, x_n pointing the voltage and ω the solar irradiance being considered Gaussian stochastic variable. The deterministic equivalent problem (4) can be specified for (1) by taking into account the hypotheses in (5) and it has the solution x_n^* and the maximum associated value of the criterion function $J_\mu^* = \mu^T x_n^*$. Based on this result, we choose $J_i < J_\mu^*$.

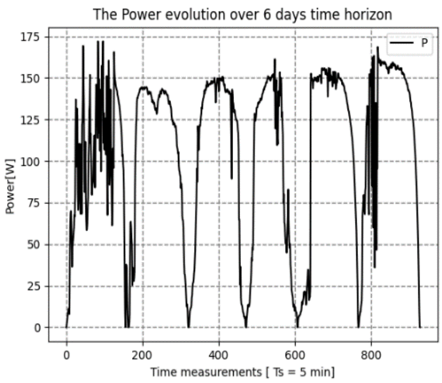

Fig. 1. The Power evolution over the specific 6 days chosen for the case studies

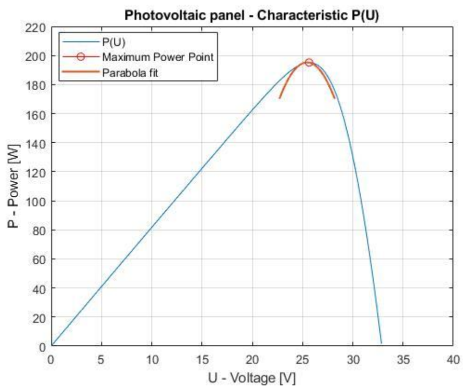

Fig. 2. The characteristic 2D, power depending on voltage

In the problem initially defined, six power characteristics that depend on voltage were considered, together with the impact of the solar irradiance ω. For the problem in (1), we defined $(A,b) \rightarrow (a,b)$ based on the datasheet characteristics of the panel [18]:

$$\begin{cases} a^T = \begin{bmatrix} 1 & -1 \end{bmatrix} \\ b^T = \begin{bmatrix} 24.15 & -21.06 \end{bmatrix} \end{cases} \tag{13}$$

The c vector approximates by the quadratic interpolation polynomials the representations in Fig. 3. The components of the random vector adhere to the

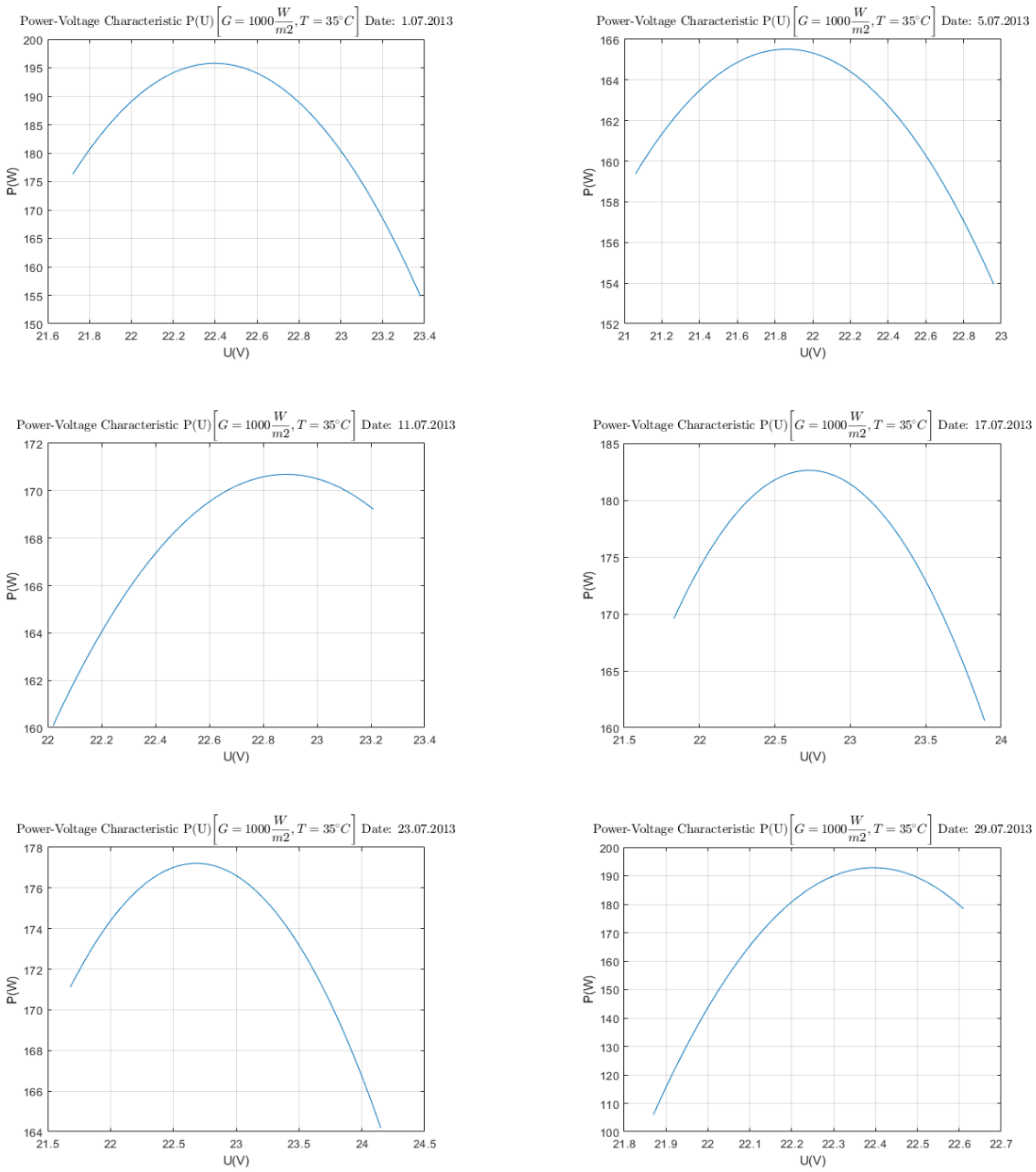

Fig.3. The relation between power and voltage with data from six days(July 1, 2013; July 5, 2013; July 11, 2013; July 17, 2013, July 23, 2013; July 29, 2013), containing values measured in the solar noon

approach based on $J(x_n) \approx c_0 x_n^2 + c_1 x_n + c_2$ approximation. Furthermore, c has a normal repartition of the average value $\mu = \left[-67.1012 \quad 3.0085\cdot 10^3 \quad -3.3543\cdot 10^4\right]$, and of the ϑ covariance matrix, $\vartheta = \begin{bmatrix} 0 & -0.0007\cdot 10^9 & 0.0074\cdot 10^9 \\ -0.0007\cdot 10^9 & 0.0297\cdot 10^9 & -0.3325\cdot 10^9 \\ -0.0074\cdot 10^9 & -0.3325\cdot 10^9 & 3.7223\cdot 10^9 \end{bmatrix}$.

The average defined problem from (6) yields an admissible optimal solution determined by applying the Cauchy Method:

$$\begin{cases} x_n^* = 22.43\ V \\ J_\mu(x_n^*) = 179.4\ W \end{cases} \tag{14}$$

By imposing, $J_i = 169W$, the new equivalent problem in (6) is defined as:

$$\max\left(\frac{-67.1012x_n^2 + 3.0085\cdot 10^3 x_n - 3.3543\cdot 10^4 - 169}{\sqrt{\begin{bmatrix} x_n^2 & x_n & 1 \end{bmatrix} \vartheta \begin{bmatrix} x_n^2 \\ x_n \\ 1 \end{bmatrix}}} \right) \tag{15}$$
$$21.06 \le x_n \le 24.15$$

The solution to the problem, $x_n^* = 22.21V$ relating to the voltage that is linked with the point of optimal utilization, was determined based on Rosen's Gradient Method [8] and the predicted result on the entire dataset was obtained in $e_{t_{MROP}} = 1.19\sec$, with an associated memory usage of $3.20GB$ and a CPU usage of 5%.

$$\alpha_r = \phi\left(\frac{169 + 67.1012x_n^2 - 3.0085\cdot 10^3 x_n + 3.3543\cdot 10^4}{\sqrt{\begin{bmatrix} x_n^2 & x_n & 1 \end{bmatrix} \vartheta \begin{bmatrix} x_n^2 \\ x_n \\ 1 \end{bmatrix}}} \right) = 0.1798 \tag{16}$$

Moreover, the minimum risk α_r attaches a confidence level of 82.02% to the criterion value $J_\mu^* = 176.5W$, greater than the imposed value $J_i = 169W$.

4.3. SVR Modeling approach (SVRM)

The second case study was build based on the Support Vector Machine for Regression Modeling scheme. The target was to develop a model that considers the variations in voltage and solar irradiance, enabling accurate predictions of the maximum output power. The evolution of the environmental stochastic factor will introduce this issue as a stochastic problem to be solved. The SVR implemented in Python 3.10.7 using the scikit-learn library version 1.1.3 is described in Fig. 4.

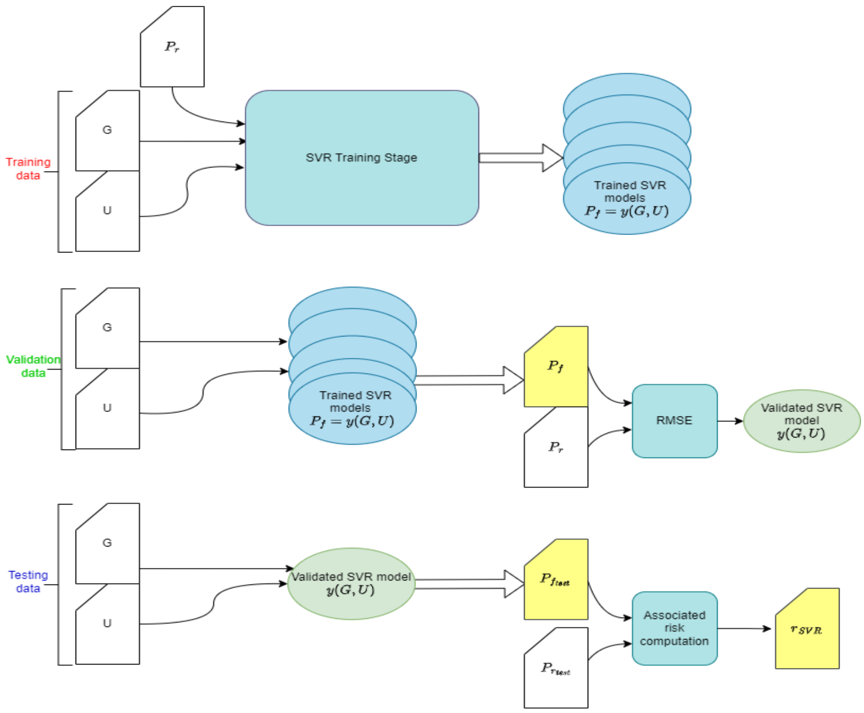

Fig. 4. SVR Modeling Strategy

The algorithm was structured in three primary stages: training, validation, and testing. The initial data, obtained for those 6 days in July, were standardized and split into 60% training values, 20% validation values, and 20% test data.

During the training stage, five models depending on $C = [0.05; 0.11; 10.05; 44.88; 104]$ regularization parameter were computed as it was defined in (8), by choosing a gaussian kernel depending on the Radial Basis Functions (RBF), also considering features the voltage together with the solar irradiance and the label known as generated power. The C selected values were narrowed down to the specified set due to exhaustive searches using an extensive grid. This analysis revealed that the implementation consumed substantial computational resources (e.g. $15.7GB$), yet the resulting improvements were not statistically significant.

In the second phase, the root-mean-square error (RMSE) associated to the defined models was computed by comparing $y_i = P_t$ (where P_t is the measured value of P) from the validation set of data with the predicted $y(x) = P_f$ (where P_f is the predicted value of P).

$$RMSE = \sqrt{\frac{1}{n_{valid}} \sum_{i=1}^{n_{valid}} \left(P_r - P_{f_{valid}} \right)} \tag{17}$$

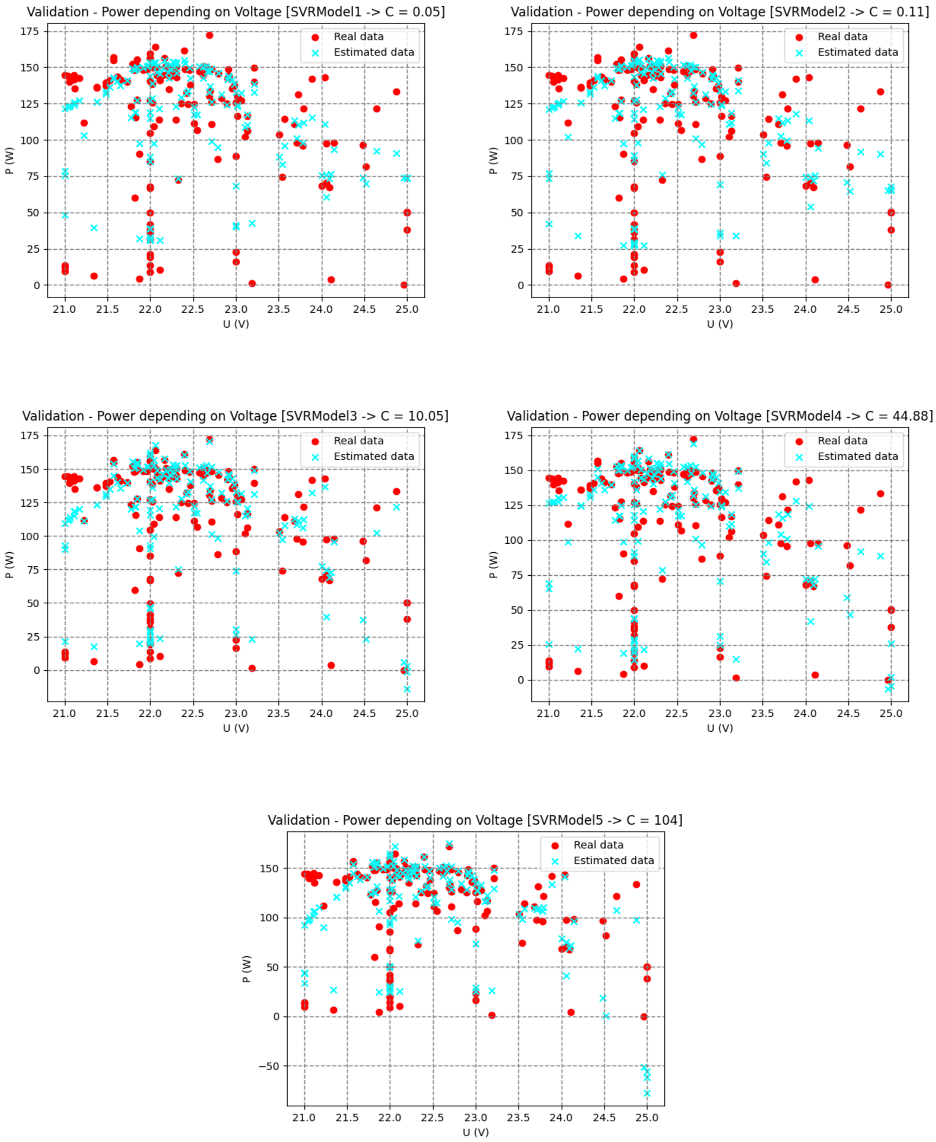

Fig.5. Validation – SVRModels applied for power prediction [red used for the real data, blue is for the estimated data]

where n_{valid} is the size of validation dataset. For each of the five regressors, the identified values for power depending on voltage can be discovered in the illustrations from Fig. 5. These charts represent the results of the predictions done [blue] during the validation stage compared to the measured power values [red]. As it can be seen, the values predicted are close to the real ones, consequently a quantitative assessment needs to be applied, to decide which of the regressors shall be used as a PV model.

Consistency of the predicted results was assessed against the actual data assuming that models have $RMSE < 0.15$. After evaluating the variation in RMSE and examining the chart representations. SVRModel4 emerged as the optimal choice. This model effectively captured the data's evolution without undue superimposition. Notably, SVRModel4 exhibited a favorable balance between accuracy and complexity, outperforming the SVRModel5.

Table 1

RMSE - Trained SVR Models [on standardized data]

Model	C	RMSE
SVRModel1	0.05	0.179
SVRModel2	0.11	0.161
SVRModel3	10.05	0.194
SVRModel4	44.88	0.138
SVRModel5	104	0.319

The best model was applied in the last test stage to predict P_{ftest} power using data totally unexplored. The predicted values were then compared to the standardized measured ones by computing $RMSE = 0.137$, the residual error res_i, represented in Fig. 6 and the SVRModel4 associated risk $r_{SVR} = 18.22\%$.

For the training of these five models and for the prediction phase, the output was achieved in approximatively $e_{t_{SVRM}} = 1.61\text{sec}$, by using $9.1GB$ of memory and 20% out of the available CPU capacity.

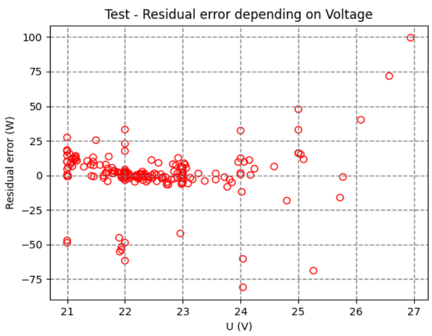

Fig. 6. Residual errors depending on voltage

5. Discussion

In addition to the previous research works, the presented comparative study offers 2 approaches to estimate the MPP by predicting the power values as suboptimal solutions for the SO. Firstly, the MROP approach relied on a specific polynomial model for power depending on voltage, evolving under solar irradiation impact, as described in the literature [8, 9]. It incorporated restrictions based on the PV electrical characteristics, particularly defining the nominal voltage domain. Secondly, the SVRM strategy trained 5 models using a RBF kernel. Unlike MROP, SVRM was agnostic to panel characteristics and did not require special restrictions. Instead, it standardized the data to mitigate the differences between features and label ranges by capturing the nonlinearities and dynamics of the PV, confirming the conclusions drawn from the literature [4,5].

6. Conclusions

In the context of optimization, both approaches aimed to find solutions for a specific SO. The problem was defined for a photovoltaic panel influenced in generation by the environmental stochastic data conditions. For both approaches, the same dataset was used considering the power's evolution based on voltage, which were concurrently influenced by solar irradiance. Regarding elapsed time, the presented results are quite close, $e_{t_{MROP}} = 1.19\sec$ and $e_{t_{SVRM}} = 1.61\sec$, but these values depend on the dataset size and the grid used for regularization factor search. Additionally, computational effort was reduced for the SVRM after selecting some regularization factors based on an initial grid search. If the first search were also considered, computation time would significantly increase. Both strategies assessed risk-associated values. For MROP, the $\alpha_r = 17.98\%$ attached to the $J_\mu^* = 176.5W$ implies that the obtained power value exceeded the imposed mean value. For SVRM, the $r_{SVR} = 18.22\%$ attached to the SVRModel4 indicates that power values are estimated around the real measured values, without explicitly determining if they are above or below those values.

The MROP approach is advisable when the electrical characteristics of the panel are well known, and computational memory resources are limited – e.g. around $4GB$. Conversely, the SVRM is preferable when only measured data are accessible, and sufficient computational resources – e.g. around $10GB$ - are available to handle a specific grid search for the regression factor. As a general guideline, achieving accurate MPP estimations in both approaches necessitates a substantial volume of data and, consequently, significant computational resources, but both of these validated results can be deployed on a real photovoltaic plant.

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