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Model-prediction of Efficiency of a Parabolic Trough Collector Using Data-Driven Soft Computing

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***Abstract*— The study highlights the need to use suitable modeling techniques to accurately predict the efficiency of parabolic trough collectors in light of their significance in renewable energy. An examination of prediction models using the Linear Regression (LR), Support Vector Regression (SVR), and Decision Tree (DT) algorithms for the efficiency of parabolic trough collectors provides insightful information about how well they work. In terms of prediction accuracy and precision, the Decision Tree model regularly performs better than its rivals throughout the training and testing phases. What sets it apart from SVR and LR models is its ability to identify minute relationships within the data. SVR performs better than LR, although it is not as exact or accurate as the DT model. Among the three models, Linear Regression has the lowest performance, underscoring its limitations in terms of capturing non-linear relationships. Given its exceptional performance, the Decision Tree model may prove to be a crucial instrument in encouraging the design and construction of solar energy systems, hence advancing the growth of sustainable development projects and renewable energy technology.**

***Keywords*— Machine learning; model prediction; regression; solar energy; decision tree.**

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I. INTRODUCTION

In order to make improvements in one's day-to-day life and overall growth, energy is essential. There is an immense supply of energy on our planet, which may be harnessed for the purpose of producing electricity. This energy comes from both conventional and non-traditional sources. On the other hand, the depletion of conventional energy sources, such as fossil fuels like coal and petroleum, presents a substantial obstacle. In order to solve this issue, researchers and scientists are looking for new sources of energy to help bridge the remaining gap [1], [2]. In order to fulfill the demands for energy on a worldwide scale, renewable energy is emerging as a viable answer. Solar energy stands out among renewable sources owing to its plentiful availability, cleanliness, absence of atmospheric pollution, eco-friendliness, and ecological sustainability. Solar energy also happens to be environmentally friendly. In spite of the fact that solar energy is only being used at a very tiny percentage (0.02%) of its capacity at the moment, it offers tremendous promise to supply the energy requirements of the world numerous times over [3], [4].

India, in particular, is characterized by high levels of direct normal irradiance and has between 250 and 300 days of sunshine that are completely clear each year. Because of this, it is very suitable for the efficient exploitation of solar energy for the generation of both heat and electricity. In order to effectively harvest solar energy, solar thermal collectors are an essential component. The radiation from the sun is collected by these devices, which then transform it into either heat energy or electrical energy. Every system that is based on solar energy must include the solar collector as its foundational component [5], [6]. An overview of the basic classifications of sun collectors is shown in Figure 1 [7], which also illustrates the many kinds of solar collectors.

By harnessing solar energy, nations can meet their energy requirements in a manner that is both environmentally responsible and reduces their dependency on limited fossil fuel supplies. Furthermore, developments in solar technology continue to improve efficiency and cost, which makes solar energy an increasingly realistic answer for satisfying the needs for energy on a worldwide scale. Within the realm of renewable energy sources, solar energy is now the most readily available and plentiful of all the available options. The use of solar thermal systems (STS) is widely regarded as one of the most effective solutions for the generation of energy from renewable sources [8], [9], [10]. Additionally, these systems contribute to the reduction of the issue of climate change. Solar energy is often recognized as a sign of clean and sustainable energy, in contrast to other kinds of energy that are not renewable and contribute to carbon dioxide emissions in the atmosphere. STS is an effort to transform solar energy towards heat in an effective manner, which would be a technique for producing environmentally friendly energy. According to the findings of many studies, the sun will continue to be a source of thermal energy for an additional four billion years. When the sky is clear, the typical amount of radiation that strikes a solar panel is around one thousand watts per square meter. This amount of radiation is adequate to provide hot water for a household. On the other hand, solar concentration panels are required in order to meet the thermal energy requirements at higher temperatures [11], [12].

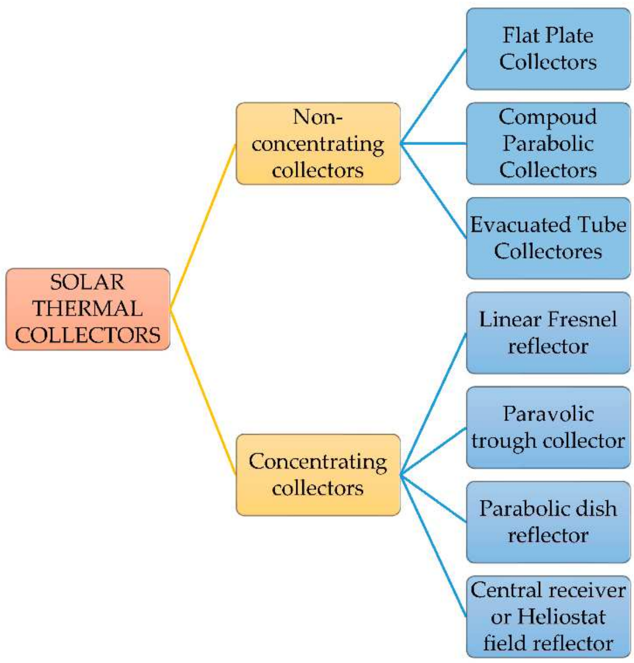


Fig. 1 Main types of solar thermal collectors [7]

There are various innovative ways to provide heating materials derived from renewable energy. It is commonly acknowledged that greenhouse gases, particularly carbon dioxide, provide severe environmental difficulties. The usage of fossil fuels is associated with higher greenhouse gas emissions, which have a larger environmental effect, cost, and health consequences. Furthermore, continued use of fossil fuels depletes resources over time. Thus, it is critical to combine fossil fuel resources with renewables and other energy storage solutions in order to lessen civilization's dependency on fossil fuels [13], [14].

Solar flat plate collectors (FPCs) are improving their thermal performance by expanding the absorber plate or increasing the heat transfer fluid (HTF) efficiency. Both techniques take into account the collector's energy and exergy efficiency. However, FPCs are renowned for having poor exergy efficiency and a restricted work extraction capability when compared to other solar collectors. An FPC's exergy efficiency may not surpass 5%, while having a maximum conversion potential of 5.3% from unconcentrated solar light. The issue of low exergy efficiency has persisted both conceptually and empirically, demanding much investigation for feasible remedies [15], [16], [17]. Blackbody absorbers, which have equal absorptance and emittance, are not suggested for efficiency improvement. Instead, spectrally selective absorbers, which have a larger absorptance than emittance, are thought to be beneficial for increasing FPC efficiency. Currently, very selective coatings are applied to copper and aluminum absorbers, providing absorptivity and emissivity values of 95% and 4%, respectively, at 100 degrees C. Researchers are also looking at the possibilities of employing other materials to obtain high selectivity at higher temperatures [16], [17].

The use of machine learning (ML) to the prediction of the efficiency of parabolic trough collectors (PTC) represents a paradigm shift in the field of research and application pertaining to renewable energy. The use of machine learning methods is justified in predictive modeling initiatives because these approaches provide benefits that are unmatched in their ability to handle the intricate and ever-changing interactions that are inherent in PTC systems. In contrast to more conventional approaches to analysis, ML algorithms are particularly effective at processing vast amounts of heterogeneous data that include a wide range of characteristics, including solar radiation, temperature outside, collector orientation, and different fluid properties [18], [19], [20], [21]. Through the use of this data, machine learning models are able to discover nuanced patterns and connections that may be beyond the comprehension of human intuition or standard statistical methods. Furthermore, machine learning makes it possible to recognize non-linear correlations and interactions amongst input variables, which improves the accuracy and resilience of forecasting algorithms for PTC efficiency [22], [23], [24]. In addition to this, machine learning makes continuous learning and adaptation possible, which enables models to develop and improve over time as new data is made accessible. This ongoing refining process guarantees that predictive models are relevant and effective in a variety of operating circumstances, which eventually results in improved use of renewable energy sources and better performance of the PTC. In light of this, the incorporation of machine learning into the predictive modeling of the efficiency of parabolic trough collectors marks a significant step forward in the field of renewable energy research. It provides insights and skills that are unmatched in their ability to solve the ever-changing difficulties and possibilities in the field of producing clean energy [25], [26], [27].

The literature in this domain reveals significant progress in experimental work. However, the numerical modeling of these systems is challenging. Hence, in this study, an attempt is made to make use of modern AI techniques like support vector regression (SVR) and decision tree (DT) for model prediction of PTC's efficiency. The performance of these ML-based models will be compared with a baseline approach of linear regression (LR). Innovatively a battery of comparing techniques including statistical methods as well as graphical plots in the form of Taylor's diagram will be used for model comparison.

II. Material and Methods

A. Test set up and testing procedure

To determine overall efficiency, the PTSC experimental platform was tested with varied nanofluid concentrations (0% to 3.0%) and mass flow rates (0.025kg/s to 0.06kg/s). Each of the nine concentrations was evaluated at all five mass flow rates. Alumina/deionized (DI) water nanofluid was held in the HTF tank and cycled through the receiver and heat exchanger by a miniature submersible pump. The PTSC's performance criteria are described below. The PTSC's efficiency is calculated as the ratio of heat absorbed by the fluid to solar energy incident on the collector aperture, using Equation (1). Additionally, the exergy efficiency is determined using Patela's equation [28], which is shown in Equation 2.

$$\eta = \frac{mC_p(T_o - T_i)}{A_c G_b} \tag{1}$$

$$\eta_{ex} = \frac{mC_p\left[T_o - T_i - T_a ln\frac{T_o}{T_i}\right]}{A_c G_b\left[1 - \frac{4}{3}\frac{T_a}{T_{sun}} + \left(\frac{T_a}{T_{sun}}\right)^4\right]} \tag{2}$$

The experimental setting defines various parameters, like η denotes energy efficiency and η_{ex} represents exergy efficiency. The flow rate of the HTF is denoted by ṁ, whereas Cp represents the HTF's specific heat. T_i denotes the HTF's entrance temperature, whereas T_o represents its exit temperature. In addition, Ta represents the ambient temperature and T_{Sun} symbolizes the Sun's surface temperature (5762 K). AC denotes the aperture area, while G_b represents the beam solar radiation.

Throughout the experiment, a variety of environmental elements and experimental circumstances are observed and documented. An anemometer with an accuracy of ±1 m/s measures wind velocity, whereas a solar power meter with an accuracy of ±10 W/m2 records sun radiation. In addition, the flow rate of the HTF is measured using a rotameter with a 1.0% accuracy. Thermocouples are used to measure nanofluid, ambient, and surface temperatures at regular intervals with an accuracy of ±0.1°C. These parameters are routinely collected at preset time intervals to guarantee that the experimental data is reliable and consistent.

B. Machine learning methods

The ML methods i.e., linear regressions, support vector regression, and decision tree were employed in this study. Following is a brief description of these methods:

1) Linear regression

Linear regression, often known as LR, is a basic statistical procedure that is used for modeling the connection that occurs among a dependent factor and a number of independent variables. Regarding regression analysis, the objective of linear regression (LR) is to build a linear connection between the variables that serve as predictors and the variable that serves as the target. The LR model assumes that this connection is shown by a straight path, which enables the prediction of events that are continuous without interruption. In order for LR to function, a line is fitted to the data points in such a way that it reduces the sum of the squared differences amongst the values that were seen and those that were anticipated. Due to the fact that it is straightforward and easy to understand, LR is a well-liked option for regression jobs in which it is anticipated that the connection between variables would be linear [29], [30].

2) Support Vector Regression

The Support Vector Regression (SVR) algorithm is a modification of the Support Vector Machine (SVM) method that has been extended for the purpose of regression analysis. In order to minimize the amount of prediction errors, the purpose of SVR is to locate the ideal hyperplane that provides the greatest fit to the data while simultaneously maximizing the margin. Instead of fitting a line that goes through as many data points as feasible, SVR focuses on generating a function that corresponds to the data within a defined margin of tolerance. This is in contrast to standard regression approaches, which concentrate on fitting a line across as many data points as possible. The support vector regression (SVR) algorithm is very helpful for datasets that include non-linear patterns, complicated connections, or high-dimensional feature spaces. Because it is able to capture non-linear correlations between variables via the use of kernel functions, SVR is adaptable enough to be used for a variety of regression problems [31], [32], [33], [34].

3) Decision Tree Regression

The non-parametric supervised learning approach known as Decision Tree Regression is used for the purpose of performing regression problems. On the other hand, decision tree regression forecasts continuous target variables, in contrast to classification decision trees, which forecast discrete class labels. The feature space is partitioned into smaller areas using decision trees, which do this by recursively dividing the data based on feature thresholds. The goal of each split is to reduce the variability of the target variable within each zone. At each node, the decision tree algorithm chooses the feature and threshold that provides the most effective division of the data. This selection is often made on the basis of criteria such as reducing the mean squared error. The decision tree regression method is favorable due to its ease of use, interpretability, and capacity to deal with both categorical and numerical data. On the other hand, decision trees are susceptible to overfitting, particularly when they are formed via the use of deep or complicated trees. The accuracy of the DT regression framework may be improved by the use of techniques like pruning and ensemble approaches such as Random Forest. These techniques can help minimize the effects of overfitting [35], [36], [37].

III. Results and Discussion

A. Data preprocessing

A correlation heatmap was created using the data from the testing phase, and it was used to estimate the degree of correlation between the data columns. Figure 2 illustrates this correlation heatmap. It might be of assistance in comprehending the impact that a variety of characteristics have on the effectiveness of the system. With a correlation value of 0.64 and 0.66, respectively, it is possible to notice that both Re numbers and Nusselt numbers have a favorable influence on effectiveness. This is something that can be observed. In a similar vein, the impacts of additional factors may be readily calculated using this method.

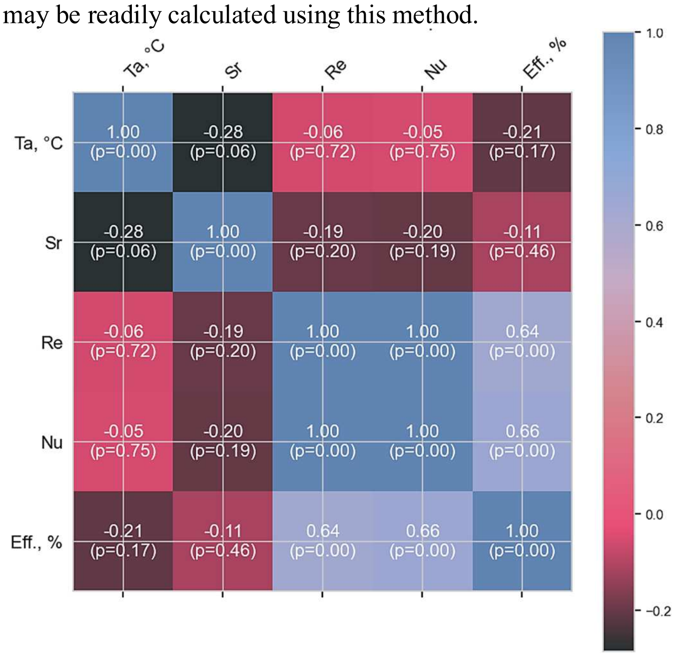


Fig. 2 Heatmap for correlation

B. Model development and evaluation

During the training phase as listed in Figure 3, the prediction models that were constructed by employing the Linear Regression (LR), Support Vector Regression (SVR), and Decision Tree (DT) algorithms were assessed based on a number of different performance criteria. Metrics such as the coefficient of determination (R), the coefficient of determination (R^2), the Kling-Gupta Efficiency (KGE), the mean squared error (MSE), and the mean absolute error (MAE) are included in this category. The accuracy and dependability of the prediction models may be shown through the use of these indicators, which give useful information. For LR, the model was able to attain a R value of 0.8680, which indicates that there is a positive linear connection between the predictor variables in the target variable that is moderately strong. The R2 value of 0.7508 indicates that the predictor variables are responsible for explaining about 75.08% of the variation in the variable that is being studied (the target variable). It is possible that LR has limits when it comes to capturing the complicated nonlinear relationships that are present in the data, despite the fact that these values exhibit fair performance. Moreover, the mean squared error (MSE) of 0.01154 and the mean absolute error (MAE) of 0.0811 represent the average squared and absolute disparities, respectively, between the values that were observed and those that were predicted.

In the case of the SVR, the model obtained higher R (0.9588) and R^2 (0.9078) values in comparison to LR. This indicates that the linear relationship between the variables is stronger and that the model provides a better explanation of the variation in the target variable. The fact that the R2 value is greater indicates that the predictor variables are responsible for about 90.78 percent of the variation in the variable that is being used as the target. In addition, the SVR model displayed lower MSE (0.00427) along with MAE (0.0519) values in comparison to the LR model, which indicates that it has greater prediction accuracy and lesser errors.

Last but not least, the DT model beat both LR and the SVR models. It achieved significantly high R values (0.9998) and R^2 values (0.9996), which indicated an almost perfect linear connection and an outstanding explanation of variation in the target variable. The DT model is characterized by its excellent accuracy and precision, as seen by the exceptionally low MSE (0.00001) with MAE (0.0008) values. These numbers indicate that there are minimal mistakes between the values that were observed and those that were predicted.

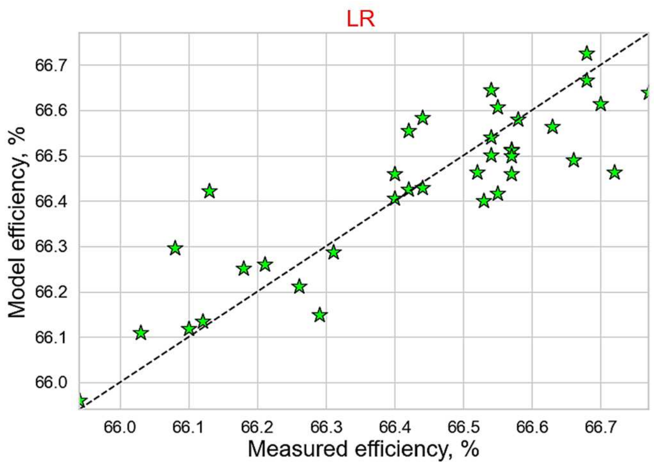
The comparative performance of all three models during model training is depicted in Figure 3a for LR-based model, Figure 3b for SVR-based model, and Figure 3c for DT-based model. The graphical representation shows that DT-based model was superior to other two models.

In short, the findings of the evaluation show that the Decision Tree model performs better than both the Linear Regression model and the Support Vector Regression model in terms of the accuracy and precision of its predictions. It may be said that the DT model provides an almost perfect match to the experimental data, with errors that are nearly nonexistent and an exceptional capacity for explanation. When it comes to accuracy and precision, the SVR model is not as good as the DT model, despite the fact that it also performs well. In general, the DT model seems to be the most appropriate option for forecasting the efficacy of the parabolic trough collector based on the experimental data that has been supplied [38], [39].

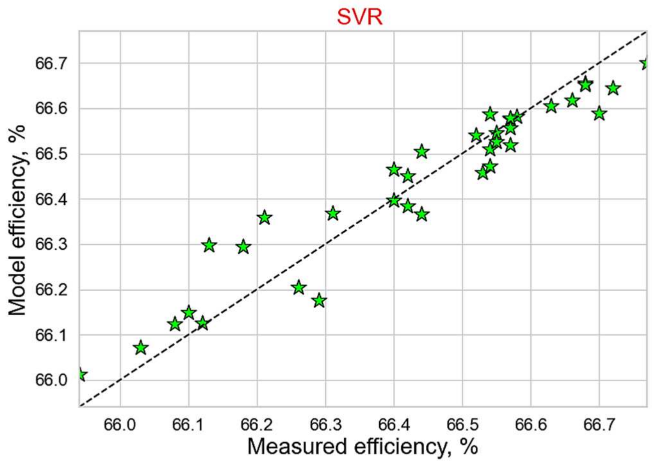
TABLE I
MODEL RESULTS ON DIFFERENT STATISTICAL METRICS

Model	R	R^2	KGE	MSE	MAE
			Model training		
LR	0.8680	0.7508	0.7867	0.01154	0.0811
SVR	0.9588	0.9078	0.8459	0.00427	0.0519
DT	0.9998	0.9996	0.9982	0.00001	0.0008
			Model testing		
LR A	0.8408	0.6507	0.8234	0.0167	0.0833
SVR	0.9657	0.9267	0.9456	0.0035	0.0413
DT	0.9959	0.9901	0.9702	0.0005	0.0143

During the model testing phase, the predictions were made on a fresh set of data. LR based model was able to acquire a R value of 0.8408, which indicates that there is a positive linear connection between the predictor variables and the target variable that is reasonably strong throughout the testing phase. The R^2 value of 0.6507 indicates that the predictor variables are responsible for explaining about 65.07% of the variation in the variable that is being studied (the target variable). Despite the fact that LR demonstrates a satisfactory level of performance, it may have difficulty capturing the intricate nonlinear connections that are present in the data. Mean squared error (MSE) of 0.0167 and mean absolute error (MAE) of 0.0833 are the average squared and absolute discrepancies, respectively, between the values that were observed and those that were predicted.



(a)



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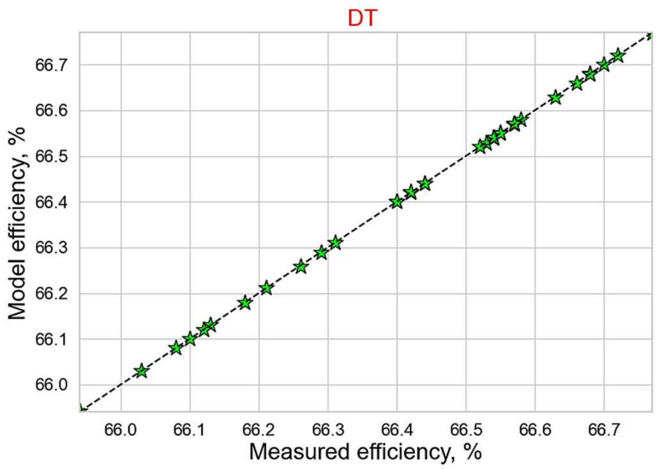
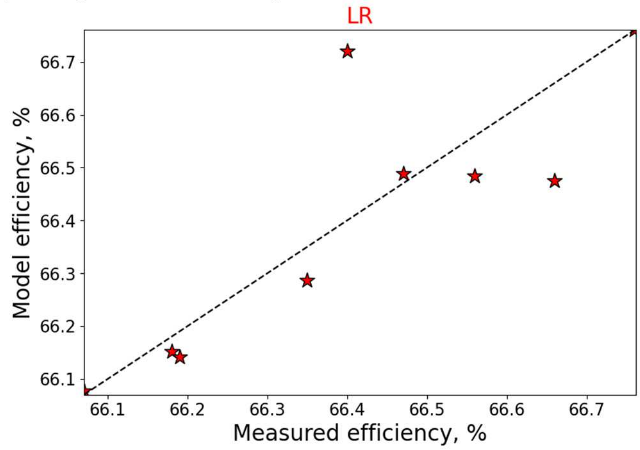


(c)

Fig. 3 Measured vs model based efficiency for (a) LR (b) SVR (c) DT based models

In the case of SVR, the model achieved higher R (0.9657) and R^2 (0.9267) values compared to LR. This indicates that the model has a stronger linear connection and provides a better explanation of the variation in the target variable during testing. Based on the higher R2 value, it may be inferred that the predictor variables are responsible for about 92.67% of the variation in the variable that is being predicted. It should also be noted that the SVR model displayed lower MSE (0.0035) and MAE (0.0413) values in comparison to the LR model, which indicates that it has greater prediction accuracy and lesser error.



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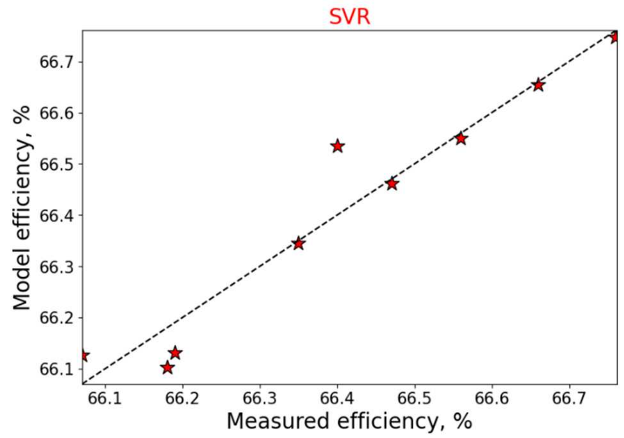

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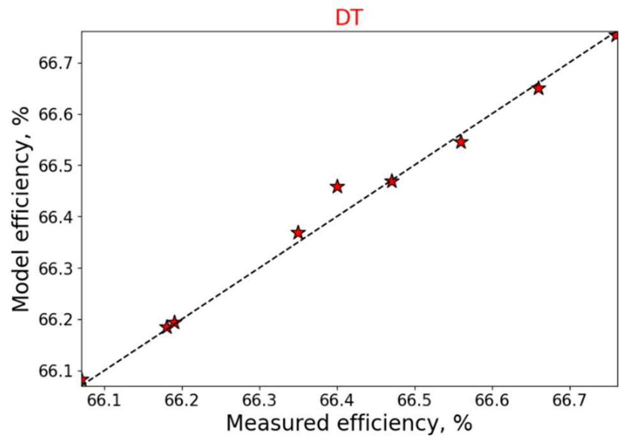


(c)

Fig. 4 Measured vs model-based efficiency for (a) LR (b) SVR (c) DT based models

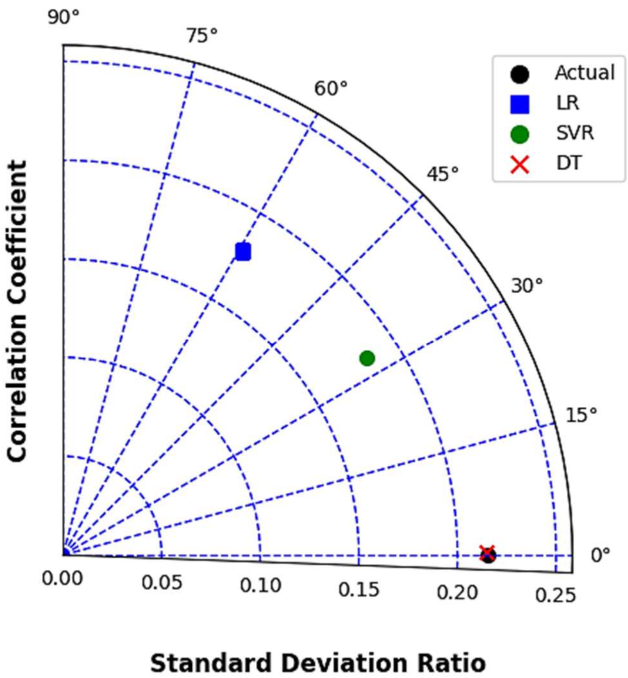
The DT model excelled both the LR and the SVR models during the testing process. It achieved high R (0.9959) and R^2 (0.9901) values, which indicates an almost perfect linear connection and an outstanding explanation of variation in the target variable. Although the MSE (0.0005) and MAE (0.0143) values are exceptionally low, they indicate that there are little error between the values that were observed and those that were anticipated. This highlights the great accuracy and precision of the DT model when it was being tested.

Figures 4a for the LR-based model, 4b for the SVR-based model, and 4c for the DT-based model show the comparative performance of all three models during testing. The graphical depiction demonstrates that the DT-based model outperformed the other two models.

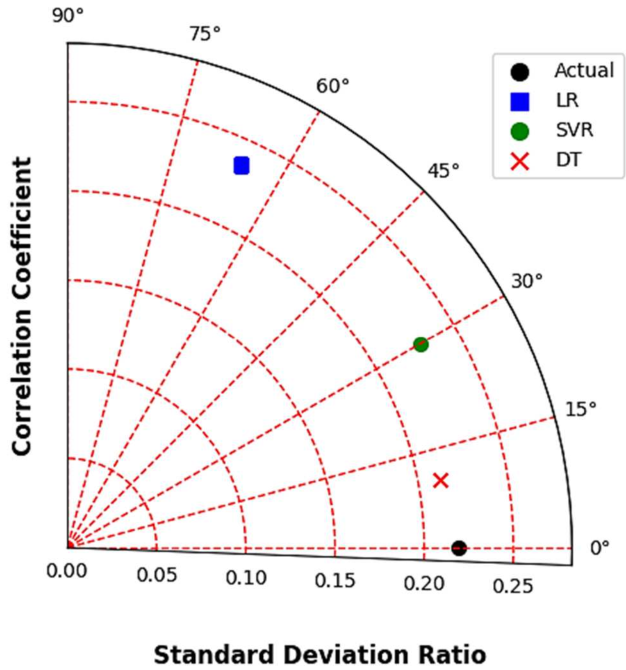
The findings of the assessment in the testing phase reveal, that the DT-based model continues to beat both the LR and SVR models in terms of the accuracy and precision of its predictions. It is clear that the DT model provides an almost perfect match to the testing data, with errors that are nearly zero and a good correlational value. When it comes to accuracy and precision, the SVR model is not as good as the DT model, despite the fact that it performs rather well during testing. In general, the DT model continues to be the most appropriate option for forecasting the performance of the parabolic trough collector based on the experimental data that was supplied during the testing phase.

C. *Model comparison with Taylor's diagram*

Taylor's diagram is a helpful tool that can be used to compare many models based on their performance across a variety of criteria at the same time. The Figure 5a depicts the Taylor's dig ram during model training while Figure 5b depicts the same for model testing phase. It can be observed that DT-based model was superior to both LR and SVR for both during training as well as testing phase [40], [41].



(a)



(b)

Fig. 5 Taylor's diagram for PTC efficiency model during (a)training (b) testing.

IV. CONCLUSION

In conclusion, the comparative study of predictive models for the efficiency of the parabolic trough collector that use the Linear Regression (LR), Support Vector Regression (SVR), and Decision Tree (DT) algorithms shows significant insights into the performance of these models. The Decision Tree model consistently emerged as the preferred alternative across both the training and testing stages, displaying the greatest levels of predicted accuracy and precision throughout the course of both phases. It differentiates itself from both SVR and LR models by virtue of its capacity to capture intricate correlations within the data and to reduce errors between the values that are predicted and those that are observed. In spite of the fact that Support Vector Regression demonstrated a performance that was substantially superior to that of Linear Regression, it was still unable to provide the same level of accuracy and precision as the Decision Tree model. The Linear Regression model, on the other hand, had the worst performance of the three models, which highlights the limits of this model in terms of its ability to capture the non-linear correlations that are present in the data. In general, the results highlight how important it is to pick proper modeling tools in order to accurately anticipate the effectiveness of parabolic trough collectors because of their relevance. The remarkable performance of the Decision Tree model indicates that it has the potential to be a useful tool for improving the development and execution of solar energy systems, which will contribute to the growth of renewable energy technology and efforts to promote sustainability.

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