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Enhancing Maximum Power Point Tracking through Ensemble Techniques

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Abstract— Maximum Power Point Tracking (MPPT) plays a pivotal role in photovoltaic (PV) solar systems, streamlining the harnessing of available power and bolstering energy conversion efficiency. Its significance lies in its alignment with the global push to heighten the efficacy of renewable energy sources. This article unfolds a meticulous examination of the predictive modeling specific to solar energy. The investigation spans various machine learning models such as Linear Regression (LR), Support Vector Regression (SVR), XGBoost Regressor, and Ensemble Learning (EL), each dissected to reveal the intricacies involved in solar energy system modeling. The research, conducted across two unique datasets—Solar Power Generation and Solar Radiation Prediction, employed rigorous statistical evaluation to uncover the distinctions in accuracy, unity, and efficacy among the models. A standout finding was the Ensemble Learning model's superior performance, notably through applying techniques like Bagging Regressor. This approach transcended the individual models in both datasets by ingeniously amalgamating the predictions of various underlying models, leading to enhanced predictive precision. This article's insights contribute considerably to the domain of solar energy modeling, elevating Ensemble Learning as a powerful instrument for refining prediction accuracy. Furthermore, the juxtaposition of various modeling methodologies unveils valuable insights into their respective trade-offs, enriching the foundation for future exploration and real-world implementations within the renewable energy landscape. In setting a novel standard in solar energy forecasting, this study also resonates with the broader objectives of sustainable energy governance and ecological preservation.
Keywords— *Solar Energy; Maximum Power Point Tracking;Ensemble Learning; Regression, PV.*

I. Introduction

The quest for efficient energy production is paramount today with increasing emphasis on renewable energy sources and reducing reliance on fossil fuels. This shift is not only influenced by environmental concerns and the finite nature of fossil fuels but also by political and economic factors, along with substantial investments in green energy technologies [1]. Currently, much of the world's energy is derived from fossil fuels, which contribute to pollution and the depletion of reserves. The demand for renewable energy, as a viable alternative for powering homes and industries, is rising [2]. Various renewable energies, such as wind, hydro, geothermal, and particularly solar energy, are experiencing rapid growth due to technological advancements and decreasing costs [3] [4]. Solar energy has emerged as a leading renewable technology, and its conversion into electricity through Photovoltaic (PV) systems is considered environmentally friendly [4]. However, challenges such as Partial Shading Conditions (PSC) can cause power loss, hotspots, and reliability issues [5]. Therefore, optimizing the output power and preventing damage is crucial for PV arrays. Maximizing power transfer from a photovoltaic generator to the load involves addressing the nonlinear characteristics of PV cells, affected by varying conditions like temperature and solar irradiance [6] [7]. Efficiency often suffers due to energy conversion challenges, but methods like maximum power point tracking (MPPT) have been developed to enhance power output [6] [7]. The high initial costs and lower conversion efficiency of PV systems, along with the susceptibility to weather fluctuations, have prompted considerable research into maximizing PV panel output under varying conditions [8] [9] [10]. Achieving a balance between the PV panel's maximum power point and load requirements is a complex but essential task [11] [12] [6]. Traditional techniques like Perturb and Observe (PaO) and Incremental Conductance (IC) have been used, though not without drawbacks [8] [13] [14] [15]. Innovative solutions, including fuzzy logic-based techniques,

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swarm optimization, and ant colony optimization, have been explored to enhance speed and stability [16] [17] [18] [19] [20] [21]. Machine learning algorithms, such as Artificial Neural Networks (ANNs) and Support Vector Regression (SVR), have also been employed to address these challenges [22] [23] [24] [25] [9] [26]. These approaches offer accuracy in estimating the maximum output power and quicker responses during testing phases. Learning or ensemble learning, which combines predictions from multiple models, is emerging as a promising field within renewable energy [27] [28]. By integrating individual models and ensemble techniques, a new frontier is being explored to maximize the efficiency and reliability of renewable energy systems, including photovoltaic systems [28] [29].

The primary aim of this article is to present and critically assess a novel methodology that incorporates diverse individual ML models, including SVR, LR, and XGBoost Regression, with EL techniques for enhancing Solar Power Generation and forecasting solar radiation. The article delves into thorough experimentation with these models, evaluating their efficacy under various environmental and operational circumstances. Specifically, the exploration is directed at understanding how different ensemble approaches can be customized for distinct scenarios to optimize solar radiation prediction and the power extracted from PV systems. By addressing this multifaceted aim, the article contributes to the ongoing evolution of renewable energy modeling, offering valuable perspectives that could transform how solar energy is predicted, harnessed, and applied. The ambition extends beyond mere theoretical exploration, aiming to convert these insights into actionable solutions that could significantly influence the renewable energy landscape.

II. LITERATURCE REVIEW

A comprehensive survey of various techniques and methodologies related to MPPT and prediction in PV systems offers a rich insight into the advances and challenges in this field. Researchers in [30] compared several maximum power point tracking (MPPT) techniques for photovoltaic (PV) systems, assessing parameters like convergence speed, cost, and efficiency. They particularly highlighted a hybrid strategy involving NN and P&O for its dynamic adaptability. In [31], the authors targeted near-perfect efficiency in PV systems by introducing an innovative method for MPPT, focusing on enhancing the Fractional Short-Circuit Current (FSCC) approach, which traditionally has significant power losses and fluctuations. An off-grid Solar Photovoltaic Water Pumping System (SPVWPS) was proposed by researchers in [32], showcasing a control strategy that combined an improved fractional open-circuit voltage (FOCV) method with scalar control, yielding excellent efficiency and power extraction. In [33], a novel apporach for longterm wind speed forecasting in India was put forth, using the k-nearest neighbors (kNN) algorithm combined with ANN, filling a research gap in energy management and wind farm planning. Researchers in [34] introduced a unique RF model to enhance MPPT in a solar energy system, achieving over 95% acceptability in testing, outperforming ANN and ANFIS methods. In [35], machine learning algorithms were applied to control a PV system at its maximum power point, with efficiencies higher than 95%, demonstrating superior performance compared to beta MPPT and ANN methods. An investigation into optimizing power harnessing under Partial Shading Conditions (PSC) was presented in [36], finding that the Weighted K-Nearest Neighbors (WK-NN) method significantly outperformed other machine learning-based algorithms. Researchers in [37] proposed enhancing the traditional P&O method for tracking the MPP, achieving an average efficiency of 99.8% in estimating the MPP after extensive training. In [35], a Decision Tree (DT) regression algorithm for MPPT in isolated PV systems was presented, showing over 93.93% efficiency despite erratic weather, outperforming other methods. A comparison of machine learning methods to forecast solar power generation was conducted in [38], reinforcing the superiority of ML techniques over statistical ones in forecasting. In [39], ANN and SVM were employed to enhance PV system performance by optimizing MPPT algorithms, with the SVM-based MPPT approach showing higher effectiveness. The application of the XGBoost regression algorithm for solar power prediction was explored in [40], demonstrating a lower error value compared to the SVM model, enhancing solar electric power generation stability. Finally, a study in [41] presented a comparative analysis of five ensemble machine learning methods for PV system applications, with CatBoost consistently outperforming other methods, showing over 99% accuracy in testing, emphasizing its effectiveness for MPPT under rapidly changing environmental conditions.

III. MATERIALS AND METHODS

A. Proposed model for chest disease detection

The proposed model takes a multifaceted approach to predicting solar energy production, weaving machine learning and ensemble learning techniques together. Two solar energy datasets are initially analyzed using Exploratory Data Analysis (EDA) [42] to identify underlying patterns and anomalies. Post EDA, the data is partitioned into training and test sets, with individual machine learning models such as LR [43], XGBoost Regressor [44] and SVR [45] being applied to the training data. Be- yond single model training; the process employs an ensemble learning technique with a Bagging Regressor. This meta-estimator fits base regressors on random subsets and then aggregates their predictions, enhancing predictive accuracy and robustness. Ultimately, the model is rigorously evaluated to assess its performance, representing a sophisticated and powerful approach to understanding solar energy production in the renewable energy sector.

B. Dataset Description

This section provides a comprehensive overview of two critical datasets related to solar power, forming the bedrock for analyzing and understanding various facets of solar energy, such as power generation and solar radiation prediction.

1)Solar Power Generation Data: The" Solar Power Generation Data" dataset1 consists of 8760 rows and 8 columns, encompassing information from two Indian solar power plants over 34 days. It is divided into power generation and sensor readings, collected at the inverter and plant levels, respectively. The data facilitates predicting power generation, identifying the need for cleaning or maintenance, and recognizing faulty equipment. Specific features include:

- Date-Hour (NMT): Specifies the date and hour of the measurement.
- Wind Speed: Indicates wind speed, affecting solar panel efficiency.
- Sunshine: Reflects the amount of sunlight, vital for solar power generation.
- AirPressure: Denotes atmospheric pressure, influencing panel performance.
- Radiation: Represents solar energy reaching the panels.
- Air Temperature: Shows ambient temperature at the location.
- Relative Air Humidity: Indicates relative humidity, impacting panel performance.
- Label:" system prediction" or predicted power generation.

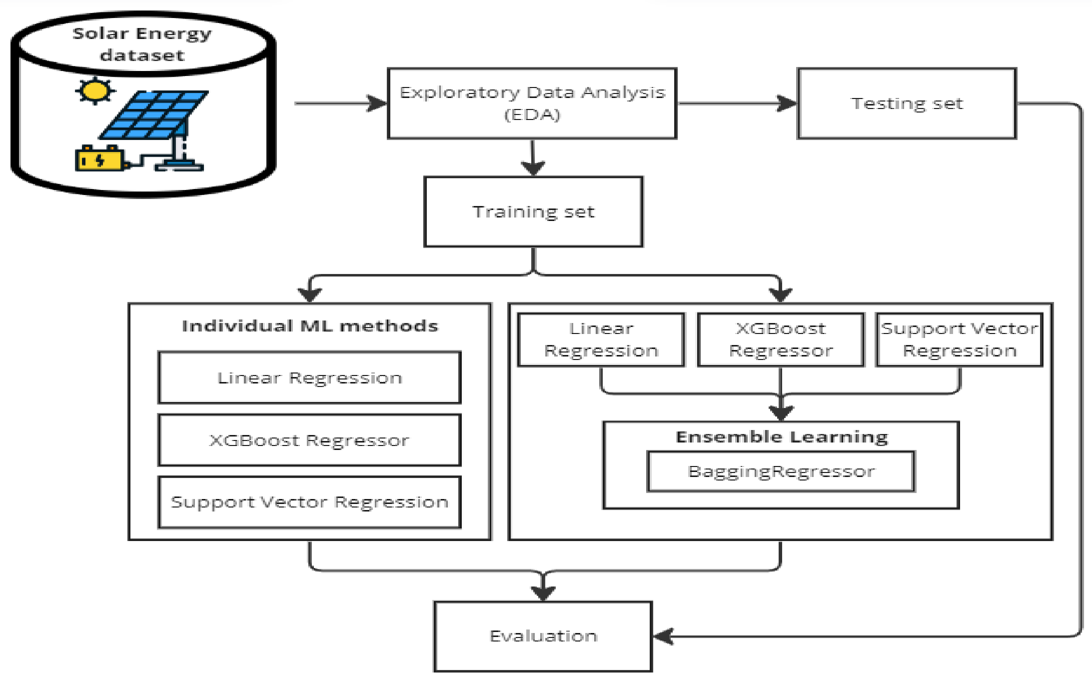

Fig.1 proposed method.

2) Solar Radiation Prediction: The" Solar Radiation Prediction" dataset2, with 32,686 rows and 11 columns, is sourced from the Space Apps Moscow event and emphasizes weather condition measurements. The dataset's goal is to forecast solar radiation levels, considering the utilization of solar energybatteries. Specific features include:

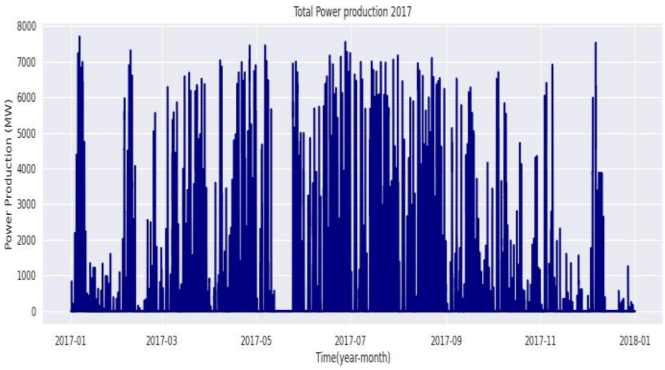

Fig. 2. Total power production in 2017.

- Temperature: The recorded temperature.
- Pressure: The atmospheric pressure recorded.
- Humidity: The humidity level recorded.
- Wind Direction (Degrees): Wind direction in degrees.
- Speed: Wind speed recorded.
- Month, Day, Hour, Minute, Second: Time-related features.
- SunPerDayHours: Duration of sunlight per day in hours.
- Label: Radiation or the level of solar radiation recorded. These datasets play an instrumental role in the evaluation of solar power generation, panel efficiency, and radiation prediction, providing insights into weather dependencies, environmental factors, and temporal aspects influencing solar energy.

C. *Exploratory Data Analysis*

The Exploratory Data Analysis (EDA) section covers two main analyses for solar energy datasets. For the Solar Power Generation Data, a line plot was created to illustrate power production throughout 2017, using seaborn library. The visualization, segmented by months or specific intervals, clearly depicts the production trends, peaks, and troughs for that year, providing valuable insights into the efficiency and challenges in power production. This graphical representation serves as a key reference tool for policymakers, energy companies, and researchers to understand the energy landscape of 2017, as presents in Fig.2.

In the EDA of Solar Radiation Prediction, feature correlation analysis and histograms with kernel density estimation (KDE) plots were conducted. By selecting variables such as” Temperature,” Pressure,”” Humidity,” ”WindDirection (Degrees),” and ”Speed,” the analysis investigates their influence on solar radiation levels. as shown in Fig.3 and Fig.4 The correlation matrix and various plots provide a concise understanding of the linear relationships, skewness, or outliers within the dataset, revealing how these meteorological variables collectively influence solar radiation levels. These insights are instrumental in predicting solar radiation based on the given features, revealing the underlying patterns and potential multicollinearity within the data, vital for subsequent modeling and analysis.

D. *Individual Machine Learning Models*

In In the exploration of solar energy within the thesis, three distinct machine learning methods are utilized to understand and predict complex relationships in the data: Linear Regression (LR), XGBoost Regressor, and Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel.

1) Linear Regression Model: LR serves as a key component, employing the LinearRegression() function to understand the linear relationships between various meteorological attributes and solar power generation. The simplicity and efficiency of LR resonate well in modeling solar energy production, providing insights into current dynamics and future applications in renewable energy.

2) XGBoost Regressor Model: The XGBoost Regressor uses the XGBRegressor() function, building on gradient boosting frameworks to improve accuracy and robustness. By handling diverse data such as temperature and wind speed, XGBoost offers computational efficiency and accurate predictions regarding solar radiation, aiding in energy efficiency and sustainability goals.

3) Support Vector Regression Model: SVR with an RBF kernel offers a sophisticated approach to predict nonlinear relationships, commonly found in solar energy data. By defining a hyperplane and using specific hyperparameters, SVR models complex interactions between atmospheric conditions and solar output, assisting in predictive maintenance, efficiency optimization, and accurate energy forecasting.

E. Ensemble Learning Model

In solar energy modeling, Ensemble learning offers a powerful approach by integrating multiple individual regression models, such as LR, SVR with an RBF kernel, and XGBoost Regressor. Combined using the Bagging Regressor method, this ensemble model leverages the strengths of each base estimator to create a more robust and accurate predictive system. Linear Regression offers simplicity, SVR brings flexibility in handling nonlinear relationships, and XGBoost adds sequential learning to boost performance. Bagging, which trains each base estimator on a random subset of data and aggregates predictions, helps reduce variance and increase resilience. This ensemble approach embraces the complex interactions of various factors in solar energy data, providing a multifaceted and nuanced understanding beyond what any single model might achieve.

IV. RESULTS AND DISCUSSION

In the following chapter, the results obtained from the comprehensive analysis of various machine learning models applied to the Solar Radiation Prediction dataset are presented and discussed. Utilizing a diverse set of statistical metrics, the performance of individual models such as LR, SVR, XGBoost Regressor, and EL has been rigorously evaluated. The discussions delve into interpreting the significance of these results, and implications of each model in the context of solar radiation prediction. This analysis provides basic insights that contribute to the overarching goal of increasing the accuracy and efficiency of solar energy forecasting, thus aligning with the broader objectives of sustainable energy management.

A. Evaluation Metrics

In the following chapter, the results obtained from the comprehensive analysis of various machine learning models applied to the Solar Radiation Prediction dataset are presented and discussed. Utilizing a diverse set of statistical metrics, the performance of individual models such as LR, SVR, XGBoost Regressor, and EL has been rigorously evaluated. The discussions delve into interpreting the significance of these results, and implications of each model in the context of solar radiation prediction. This analysis provides basic insights that contribute to the overarching goal of increasing the accuracy and efficiency of solar energy forecasting, thus aligning with the broader objectives of sustainable energy management.

B. Evaluation Result

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1. EVALUATION RESULTS WITH SOLAR POWER GENERATION DATASET (Data 1)

The evaluation of individual methods with the Solar Power Generation Dataset serves as a critical component in assessing the effectiveness of various machine learning models applied to the solar energy prediction task. Focusing on models such as Linear Regression, Support Vector Regression (SVR), and XGBoost Regressor, this evaluation encompasses diverse quantitative measures including RMSE, R^2, MSE and MAE. These metrics provide a comprehensive perspective on how well the individual methods fit the specific characteristics of the Solar Power Generation Dataset.

- **Linear Regression**

The assessment of the Linear Regression (LR) model within the framework of solar energy analysis is elucidated through a comprehensive evaluation of its performance, as depicted in Table 1. The metrics presented in the table serve as vital indicators of the LR model's predictive capabilities in the context of solar energy outcomes. Notably, the RMSE is measured at 0.0721, reflecting the model's accuracy in predicting solar related variables. The R^2 stands at 0.6401, signifying a substantial degree of variability captured by the LR model. Additionally, the MSE is calculated at 0.00519, further attesting to the model's precision. The MAE of 0.0410 underscores the average magnitude of the errors, offering a practical insight into the LR model's performance.

Fig.3 Actual vs Predicted Values of LR with Data 1.

- **Support Vector Regression**

The evaluation of the SVR model in the realm of solar energy prediction is presented with precision in Table 2. This assessment involves a thorough scrutiny of the model's performance, with various statistical metrics shedding light on its predictive capabilities. Notably, the RMSE is reported at 0.0983, indicating the level of accuracy in the SVR model's predictions for solar energy related variables. The R^2 stands at 0.330, emphasizing the extent of variability captured by the SVR model. Furthermore, the MSE is calculated as 0.00967, providing additional insights into the model's precision. The MAE is recorded at 0.07810, offering a practical measure of the average magnitude of errors in the SVR model's predictions.

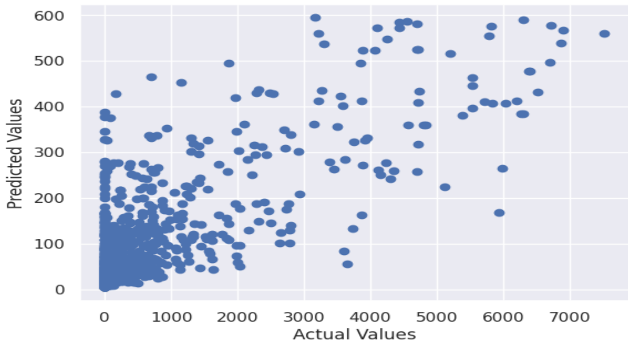


Fig.4 Actual vs Predicted Values of SVR with Data1.

- **XGBoost Regressor**

The evaluation of the XGBoost Regressor model in the realm of solar energy prediction reveals a robust performance characterized by strong predictive accuracy and efficiency. The model's ability to elucidate approximately 70.62% of the dependent variable's variance is particularly noteworthy, as indicated by an R^2 value of 0.70621. Table 3 further outlines the model's performance metrics, with a RMSE of 0.72251, attesting to the accuracy of its predictions. The MSE is reported at 0.00522, underscoring the model's precision in capturing solar energy related outcomes. Additionally, the MAE is noted at 0.03892, indicating a low average magnitude of errors in the XGBoost Regressor's predictions. These results collectively affirm the suitability and effectiveness of the XGBoost Regressor model in the solar energy prediction task, providing valuable insights for the broader research context.

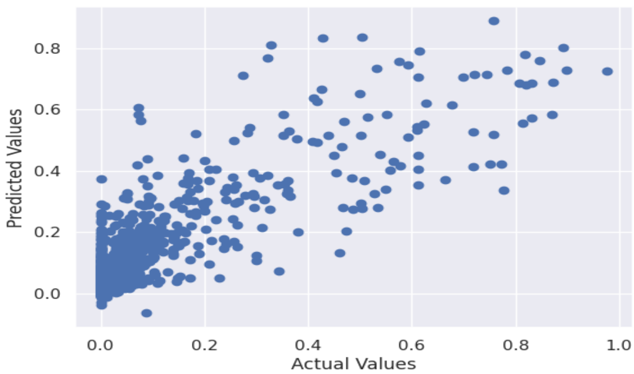


Fig.5 Actual vs Predicted Values of XGBoost Regressor with Data 1.

- **Ensemble Leaning**

The results of the EL model made in evaluating the proposed solar energy prediction framework manifest a significant improvement in predictive performance. By leveraging the collective strengths of various underlying models, the ensemble approach has yielded an RMSE value of 0.06013, which demonstrates robust accuracy in prediction. The R2 stands at 0.75, indicating that nearly 75% of the variance in the dependent variable is predictable from the independent variables, an important achievement in model fitting. Moreover, the MSE and MAE values are 0.003616 and 0.02347 respectively, further attesting to the model's effectiveness in minimizing the error in predictions. These metrics collectively articulate the success of the Ensemble Learning model in achieving a nuanced and more accurate understanding of solar energy production, underscoring its utility and potential in the renewable energy sector.

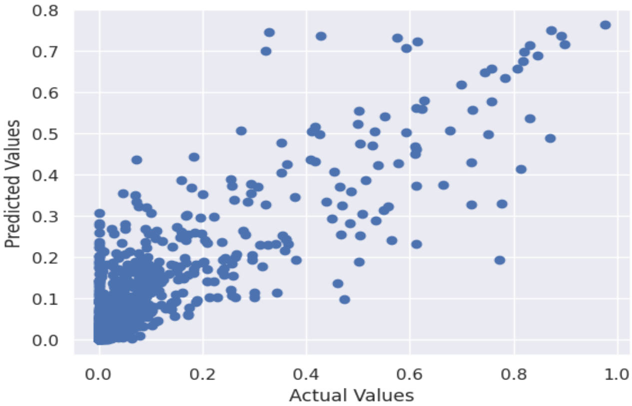
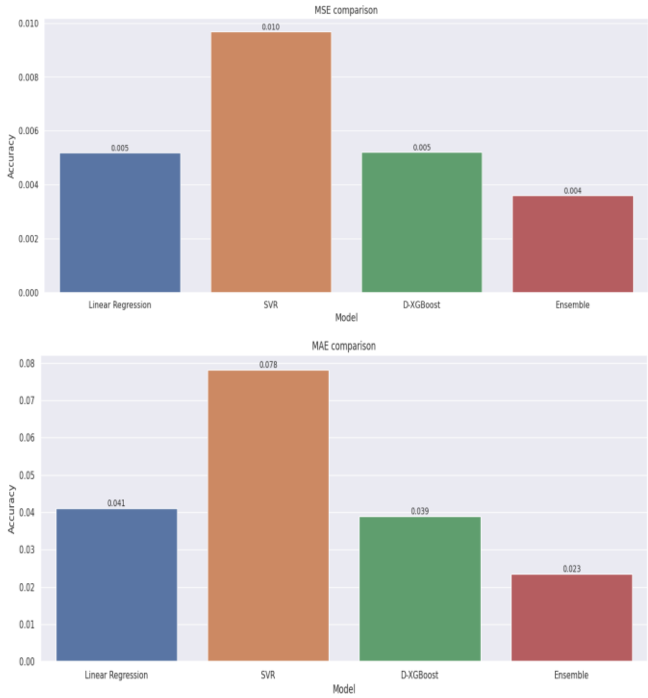


Fig.6 Actual vs Predicted Value of Ensemble Learning with Data 1.

By aggregating predictions from multiple underlying models, it explained approximately 74.48% of the variance in power generation and achieved the lowest MSE and MAE values. The EL model demonstrated outstanding performance, showcasing its potential as the preferred choice for accurate power generation predictions.



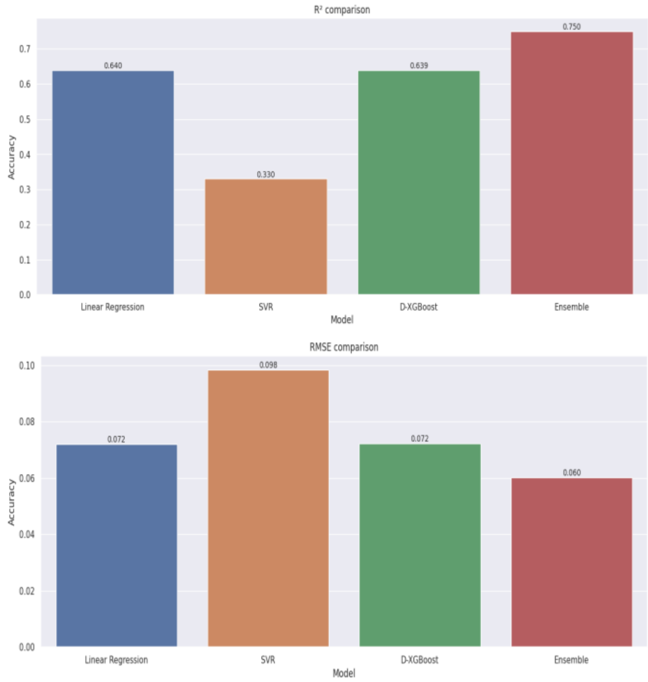


Fig.7 Comparison results with Solar Power Generation Dataset.

2. EVALUATION RESULTS WITH SOLAR RADIATION PREDICTION DATASET (Data 2)

The evaluation of individual methods in the context of predicting solar radiation serves as a foundational step toward understanding the intricacies and dynamics that govern the behavior of solar energy phenomena. Utilizing the Solar Radiation Prediction dataset, various individual models, including LR, SVR, and XGBoost Regressor, were carefully tested to decipher their capabilities and limitations. Each model was subjected to tough testing and validation, with results expressed through diverse metrics.

- **Linear Regression**

The evaluation of the LR model in the context of predicting solar radiation with a specific dataset indicates a commendable fit, elucidating 62.37% of the observed variance. The model's performance is further scrutinized through various metrics, as outlined in Table 5, offering a comprehensive view of its strengths and areas for potential improvement. The RMSE is reported at 0.12083, providing insight into the accuracy of the LR model's predictions. The R^2 stands at 0.62371, reflecting a substantial proportion of the variability in the dependent variable accounted for by the model. The MSE is calculated at 0.01459, contributing additional perspective on the model's precision. Furthermore, the MAE is noted at 0.09130, providing a measure of the average magnitude of errors in the LR model's predictions. These metrics collectively offer a nuanced understanding of the LR model's performance, highlighting its strengths in explaining solar radiation variations while also indicating areas where refinement may enhance predictive accuracy.

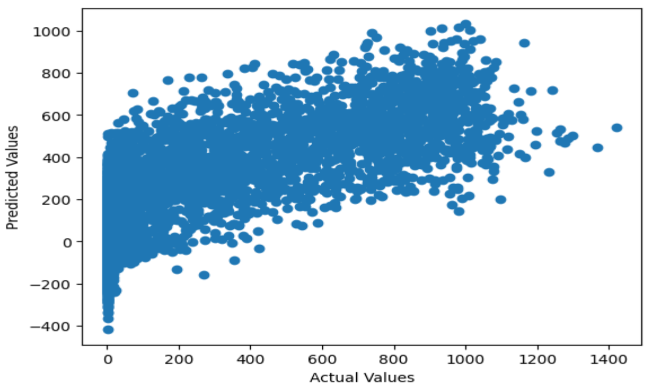


Fig.8 Actual vs Predicted Values of LR with Data 2.

- **Support Vector Regression**

The evaluation results of the SVR model for solar radiation prediction reveal suboptimal performance characterized by high prediction errors, a weaker fit, and substantial discrepancies in predictions. The Root RMSE is reported at 0.25432, indicating a notable level of inaccuracy in the SVR model's predictions. The R^2 is documented at 0.73084, reflecting a weaker fit compared to ideal predictive models. The MSE is calculated at 0.01044, further emphasizing the model's challenges in achieving precise predictions. Additionally, the MAE is noted at 0.07391, indicating a considerable average magnitude of errors in the SVR model's predictions. These metrics collectively underscore the limitations of the SVR model in the solar radiation prediction task and emphasize the necessity for further refinement or exploration of alternative models to enhance predictive accuracy and overall model performance.

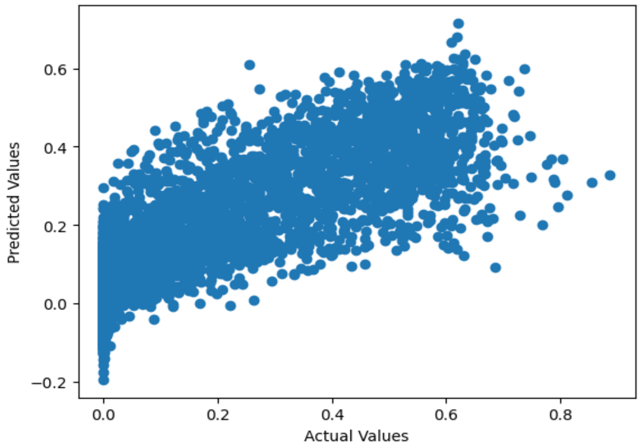


Fig.9 Actual vs Predicted Values of SVR with Data2.

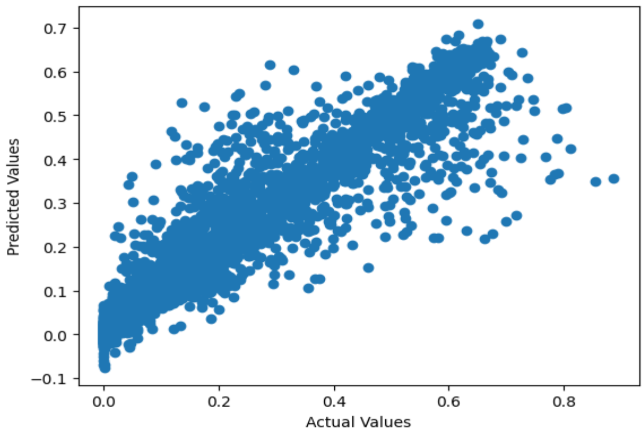


Fig.10 Actual vs Predicted Values of XGBoost Regressor with Data 2.

- **Ensemble Learning**

The evaluation results of the Ensemble Learning model applied to the Solar Radiation Prediction dataset showcase a remarkable improvement in performance, underscoring the efficacy of combining multiple predictive models. The model demonstrates high prediction accuracy, as evidenced by an RMSE of 0.27349, indicating reduced error in predicting solar radiation. Impressively, the R^2 stands at 0.93054, signifying that the model explains approximately 93.05% of the variance in solar radiation an indication of an outstanding fit. The MSE and MAE values further substantiate the model's excellence, recorded at 0.00269 and 0.01986, respectively. These metrics collectively affirm the Ensemble Learning model as a powerful and effective tool for solar radiation prediction. By harnessing the strengths of diverse models, it achieves superior results and emerges as a valuable asset in the domain of solar energy prediction.

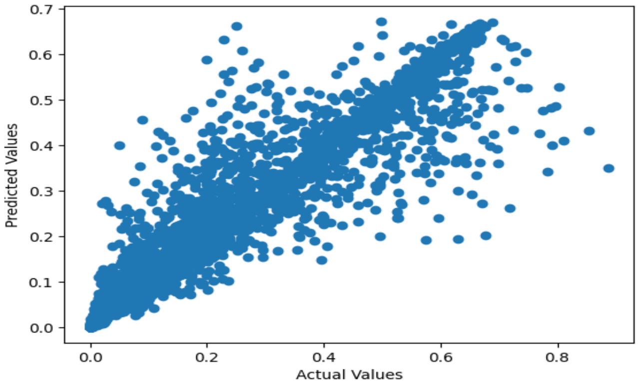
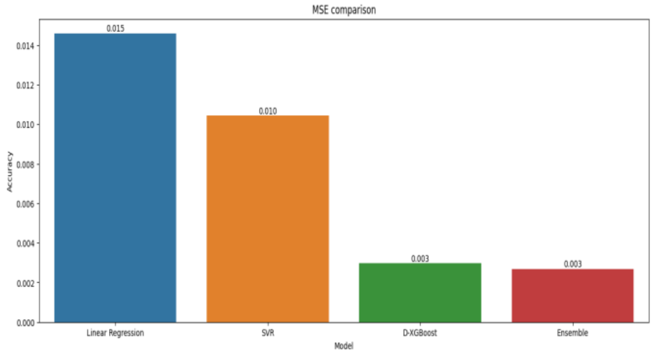
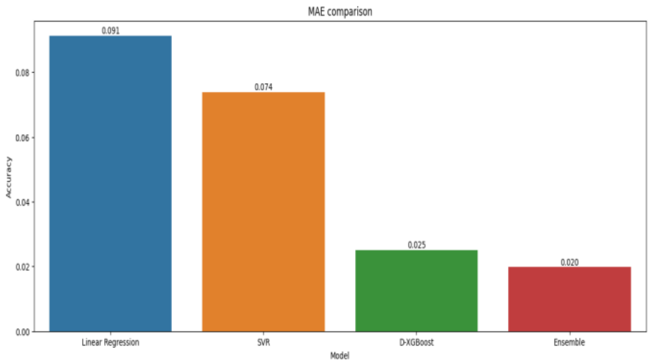
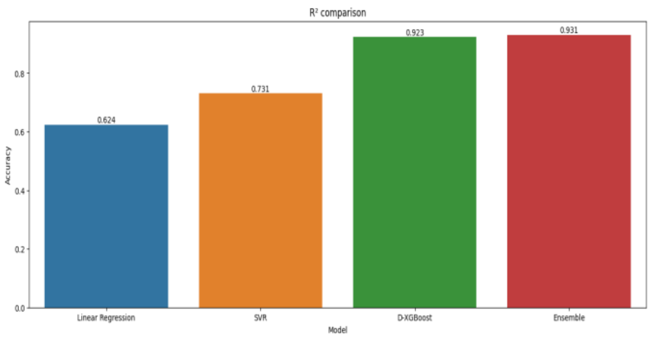


Fig.11 Actual vs Predicted Value of Ensemble Learning with Data 2.

The Ensemble Learning approach demonstrated enhanced prediction accuracy, precision, and robustness, explaining a remarkable 93.02% of the variance in solar radiation through a synergistic integration of different models while mitigating their weaknesses.







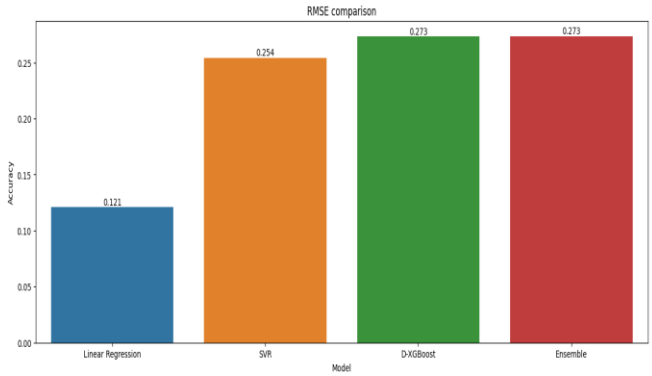


Fig.13 Comparison results with Solar Radiation Prediction dataset.

V. Conclusion

Solar energy, derived from the sun's radiant power, stands as a vast and sustainable energy source, offering an eco-friendly substitute to conventional fossil fuels. This thesis has delved into the critical task of predicting solar radiation, a cornerstone in converting solar energy into electricity. The research has shed light on each model's capabilities and restrictions through an exhaustive examination of various machine learning models, including LR, SVR, XGBoost Regressor, and Ensemble Learning (EL). Ensemble Learning, notably, exhibited extraordinary compatibility with actual solar radiation data. The outcomes of this investigation extend beyond academic interest, resonating with practical applications vital for energy producers, governmental bodies, and technology innovators. The improved precision in solar radiation predictions, as underscored by the findings, paves the way for better energy production, grid coordination, and energy preservation strategies. Such improvements catalyze cost reductions, foster more comprehensive acceptance of solar technology, and bolster global climate change mitigation efforts. Looking ahead, the promising avenues stemming from this thesis are manifold. The notably effective EL model offers scope for refinement by exploring varied base models and techniques to enhance prediction precision for distinct locations and weather circumstances. Incorporating more detailed weather data and utilizing deep learning and neural networks present additional paths for advancement. Collaborative efforts with industrial partners may hasten the transformation of these predictive models into real-world applications, driving sustainable energy strategies and policymaking forward. These prospective endeavors harbor the promise of substantial progress in solar energy forecasting, aligning it with overarching aims of ecological conservation and a worldwide shift in energy paradigms.

References

[1] Paul Ekins, Michael J Bradshaw, and Jim Watson. *Global energy: Issues, potentials, and policy implications*. Oxford University Press, 2015.

[2] Panwar, N. L., Kaushik, S. C., & Kothari, S. (2011). Role of renewable energy sources in environmental protection: A review. Renewable and Sustainable Energy Reviews, 15(3), 1513–1524.

[3] Brewer, W. D., Wengenmayr, R., & Bührke, T. (2013). "Renewable energy: Sustainable energy concepts for the energy change." John Wiley & Sons.

[4] Mekhilef, S., Saidur, R., & Safari, A. (2011). A review on solar energy use in industries. Renewable and Sustainable Energy Reviews, 15(4), 1777–1790.

[5] Ma, J., Jiang, H., Huang, K., Bi, Z., & Man, K. L. (2017). Novel field-support vector regression-based soft sensor for accurate estimation of solar irradiance. IEEE Transactions on Circuits and Systems I: Regular Papers, 64(12), 3183–3191.

[6] De Brito, M. A. G., Galotto, L., Sampaio, L. P., Melo, G. A. e., & Canesin, C. A. (2012). Evaluation of the main MPPT techniques for photovoltaic applications. IEEE Transactions on Industrial Electronics, 60(3), 1156–1167.

[7] Katche, M. L., Makokha, A. B., Zachary, S. O., & Adaramola, M. S. (2023). A comprehensive review of maximum power point tracking (MPPT) techniques used in solar PV systems. Energies, 16(5), 2206.

[8] Farhat, M., Barambones, O., & Sbita, L. (2015). Efficiency optimization of a DSP-based standalone PV system using a stable single input

fuzzy logic controller. Renewable and Sustainable Energy Reviews, 49, 907–920.
[9] Shi, J., Lee, W.-J., Liu, Y., Yang, Y., & Wang, P. (2012). Forecasting power output of photovoltaic systems based on weather classification and support vector machines. IEEE Transactions on Industry Applications, 48(3), 1064–1069.
[10] Huang, Y., Lu, J., Liu, C., Xu, X., Wang, W., & Zhou, X. (2010). Comparative study of power forecasting methods for PV stations. In 2010 International Conference on Power System Technology, pages 1–6. IEEE.
[11] Takruri, M., Farhat, M., Sunil, S., Ramos-Hernanz, J. A., & Barambones, O. (2020). Support vector machine for photovoltaic system efficiency improvement. Journal of Sustainable Development of Energy, Water and Environment Systems, 8(3), 441–451.
[12] Farhat, M., Barambones, O., & Sbita, L. (2017). A new maximum power point method based on a sliding mode approach for solar energy harvesting. Applied Energy, 185, 1185–1198.
[13] Veerachary, M., Senjyu, T., & Uezato, K. (2003). Neural-network-based maximum-power-point tracking of coupled-inductor interleaved-boost-converter-supplied PV system using fuzzy controller. IEEE Transactions on Industrial Electronics, 50(4), 749–758.
[14] Mohammed, S. S., Devaraj, D., & Ahamed, T. P. I. (2016). A novel hybrid maximum power point tracking technique using perturb & observe algorithm and learning automata for solar PV system. Energy, 112, 1096–1106.
[15] Piegari, L., Rizzo, R., Spina, I., & Tricoli, P. (2015). Optimized adaptive perturb and observe maximum power point tracking control for photovoltaic generation. Energies, 8(5), 3418–3436.
[16] Chen, Y.-T., Jhang, Y.-C., & Liang, R.-H. (2016). A fuzzy-logic based auto-scaling variable step-size MPPT method for PV systems. Solar Energy, 126, 53–63.
[17] Alajmi, B. N., Ahmed, K. H., Finney, S. J., & Williams, B. W. (2010). Fuzzy-logic-control approach of a modified hill-climbing method for maximum power point in microgrid standalone photovoltaic system. IEEE Transactions on Power Electronics, 26(4), 1022–1030.
[18] Algarín, C. R., Giraldo, J. T., & Alvarez, O. R. (2017). Fuzzy logic based MPPT controller for a PV system. Energies, 10(12), 2036.
[19] Hassan, S. Z., Li, H., Kamal, T., Arifoglu, U., Mumtaz, S., & Khan, L. (2017). Neuro-fuzzy wavelet based adaptive MPPT algorithm for photovoltaic systems. Energies, 10(3), 394.
[20] Hou, W., Jin, Y., Zhu, C., Li, G., et al. (2016). A novel maximum power point tracking algorithm based on glowworm swarm optimization for photovoltaic systems. International Journal of Photoenergy, 2016.
[21] Titri, S., Larbes, C., Toumi, K. Y., & Benatchba, K. (2017). A new MPPT controller based on the ant colony optimization algorithm for photovoltaic systems under partial shading conditions. Applied Soft Computing, 58, 465–479.
[22] Messalti, S., Harrag, A., & Loukriz, A. (2017). A new variable step size neural networks MPPT controller: Review, simulation and hardware implementation. Renewable and Sustainable Energy Reviews, 68, 221–233.
[23] Ramos-Hernanz, J. A., Barambones, O., Lopez-Guede, J. M., Zamora, I., Eguia, P., Farhat, M., et al. (2016). Sliding mode real-time control of photovoltaic systems using neural estimators. International Journal of Photoenergy, 2016.
[24] Kofinas, P., Dounis, A. I., Papadakis, G., & Assimakopoulos, M. N. (2015). An intelligent MPPT controller based on direct neural control for partially shaded PV system. Energy and Buildings, 90, 51–64.
[25] Bouarroudj, N., Boukhetala, D., Feliu-Batlle, V., Boudjema, F., Benlahbib, B., & Batoun, B. (2019). Maximum power point tracker based on fuzzy adaptive radial basis function neural network for PV-system. Energies, 12(14), 2827.
[26] Wu, Q., & Peng, C. (2016). Wind power generation forecasting using least squares support vector machine combined with ensemble empirical mode decomposition, principal component analysis and a bat algorithm. Energies, 9(4), 261.
[27] Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. Renewable and Sustainable Energy Reviews, 144, 110992.
[28] Sagi, O., & Rokach, L. (2018). Ensemble learning: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1249.

[29] Gu, G. H., Noh, J., Kim, I., & Jung, Y. (2019). Machine learning for renewable energy materials. Journal of Materials Chemistry A, 7(29), 17096–17117.

[30] Devarakonda, A. K., Karuppiah, N., Selvaraj, T., Balachandran, P. K., Shanmugasundaram, R., & Senjyu, T. (2022). A comparative analysis of maximum power point techniques for solar photovoltaic systems. Energies, 15(22), 8776.

[31] Nzoundja Fapi, C. B., Wira, P., Kamta, M., Tchakounte, H., & Colicchio, B. (2021). Simulation and dSPACE hardware implementation of an improved fractional short-circuit current MPPT algorithm for photovoltaic system. Applied Solar Energy, 57, 93–106.

[32] Hmidet, A., Subramaniam, U., Elavarasan, R. M., Raju, K., Diaz, M., Das, N., Mehmood, K., Karthick, A., Muhibbullah, M., & Boubaker, O. (2021). Design of efficient off-grid solar photovoltaic water pumping system based on improved fractional open circuit voltage MPPT technique. International Journal of Photoenergy, 2021, 1–18.

[33] Azeem, A., Fatema, N., & Malik, H. (2018). k-NN and ANN based deterministic and probabilistic wind speed forecasting intelligent approach. Journal of Intelligent & Fuzzy Systems, 35(5), 5021–5031.

[34] Shareef, H., Mutlag, A. H., Mohamed, A., et al. (2017). Random forest-based approach for maximum power point tracking of photovoltaic systems operating under actual environmental conditions. Computational Intelligence and Neuroscience, 2017.

[35] Mahesh, P. V., Meyyappan, S., & RamakoteswaraRao, A. (2022). Maximum power point tracking with regression machine learning algorithms for solar PV systems. International Journal of Renewable Energy Research (IJRER), 12(3), 1327–1338.

[36] Nkambule, M. S., Hasan, A. N., Ali, A., Hong, J., & Geem, Z. W. (2021). Comprehensive evaluation of machine learning MPPT algorithms for a PV system under different weather conditions. Journal of Electrical Engineering & Technology, 16, 411–427.

[37] Memaya, M., Moorthy, C. B., Tahiliani, S., & Sreeni, S. (2019). Machine learning based maximum power point tracking in solar energy conversion systems. International Journal of Smart Grid and Clean Energy, 8(6), 662–669.

[38] Mukherjee, D., Chakraborty, S., Guchhait, P. K., & Bhunia, J. (2020). Machine learning based solar power generation forecasting with and without MPPT controller. In 2020 IEEE 1st International Conference for Convergence in Engineering (ICCE), pages 44–48. IEEE.

[39] Kumar, P., Viswambharan, V. K., & Pillai, S. (2023). Performance analysis of maximum power point tracking of PV systems using artificial neural networks and support vector machines. In 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), pages 511–515. IEEE.

[40] Obiora, C. N., Ali, A., & Hasan, A. N. (2021). Implementing extreme gradient boosting (XGBoost) algorithm in predicting solar irradiance. In 2021 IEEE PES/IAS PowerAfrica, pages 1–5. IEEE.

[41] Omer, Z. M., & Shareef, H. (2022). Comparison of decision tree based ensemble methods for prediction of photovoltaic maximum current. Energy Conversion and Management: X, 16, 100333.

[42] Camizuli, E., & Carranza, E. J. (2018). Exploratory data analysis (EDA). The encyclopedia of archaeological sciences, 1-7.

[43] Su, X., Yan, X., & Tsai, C.-L. (2012). Linear regression. Wiley Interdisciplinary Reviews: Computational Statistics, 4(3), 275-294.

[44] Zhang, X., et al. (2020). Predicting missing values in medical data via XGBoost regression. Journal of healthcare informatics research, 4, 383-394.

[45] Awad, M., et al. (2015). Support vector regression. Efficient learning machines: Theories, concepts, and applications for engineers and system designers, 67-80.