PREDICTIVE CLARITY IN ENERGY ANALYTICS: XAI-ENHANCED SOLAR FORECASTING IN SIBERIA

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Abstract

This study unveils a robust LASSO-RFR hybrid model for solar power prediction in Siberia, significantly enhancing predictive accuracy and reducing MSE, with an R-squared of 85.9 %. Employing LIME and SHAP for XAI, it foregrounds feature contributions, fostering transparent, reliable forecasting in extreme climates.

Key words: hybrid machine learning models, XAI implementation, climate data analysis.

Introduction

Explainable AI (XAI) is rapidly emerging as a crucial area of research, becoming an essential aspect of AI systems to ensure their decisions are understandable by human users. Reference [1] defines explainability as the characteristic of a system to offer a logical reasoning process that ensures comprehension and underscores the necessity of a human-centered approach. XAI techniques strive to elucidate the processes through which decisions are made and the foundational principles behind those decisions. In recent decades, global energy demands have experienced a significant rise, accompanied by a shift towards sustainable, clean, and renewable energy due to climate change. Studies have demonstrated the potential of applying artificial intelligence in solar systems for predictive maintenance, load forecasting, demand response, etc. However, these advancements have been limited by a lack of explainability, often termed as "a black box." References [2] and [3] have both highlighted the capacity of XAI models such as LIME (Local Interpretable Model-agnostic Explanation), ELI5 (Explain Like I'm 5), and SHAP (SHapley Additive exPlanation) to enhance the explainability and transparency of AI models. These tools can identify important input features and elucidate the relationship between them and the predicted output. Additional contributions have improved the efficiency and interpretability of solar PV power generation forecasting models, including artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) [4, 5]. Several publications have demonstrated the application of Explainable AI (XAI) for both probabilistic and deterministic photovoltaic (PV) forecasting. Reference [6] introduced an adaptive Bayesian-based model for PV forecasting, emphasizing transparency and interpretability. This approach allows human users to grasp the model's decision-making logic. Reference [7] developed an innovative hybrid model combining wavelet transform and deep convolution neural network for deterministic PV power forecasting and further integrated this deterministic method with a probabilistic model using spine quantile regression.

Hybrid models employing recurrent neural networks and long short-term memory have been utilized in forecasting day-ahead and hour-ahead PV power generation. Reference [8] proposed a robust, flexible, and more accurate model for forecasting power generation across three different plants, demonstrating superior performance metrics compared to existing techniques. This model was further enhanced by [9] through a convolutional self-attention mechanism based on LSTM, with additional improvements by [10] incorporating an attention mechanism based on a CNN-LSTM neural network.

The adoption of XAI techniques and tools, which are explainable, transparent, and interpretable to human users, can enhance decision-making and the development of more accurate, efficient, and effective systems. Engaging XAI to elucidate AI model operations for human users can promote the models' application in real-world scenarios, thereby boosting user trust and reliability in AI systems.

Research Methods

LASSO-RFR Hybrid Framework and Explainability

In this work, we explore a LASSO-RFR hybrid approach for enhancing predictive accuracy in environmental data analysis. This methodology synergizes LASSO regression's feature selection prowess with the RFR's robustness in handling complex, non-linear data structures. The LASSO model serves as a preliminary filter, identifying and eliminating less impactful features, thereby simplifying the dataset. Subsequently, the refined dataset is analyzed using RFR, focusing on capturing the intricate relationships between the remaining features and the target variable [11]. This dual-stage process not only improves model performance but also ensures a balance between simplicity and predictive accuracy, mitigating over-fitting concerns. The hybrid approach demonstrates significant improvements over traditional single-model techniques, offering a more reliable tool for environmental forecasting and analysis.

The dataset used for the analysis was obtained from the TOR station, Tomsk, Siberia. Measurements were obtained for the following: DATETIME = Date-Time; "fonsr" = Solar Radiation; "font10m" = Temperature; "fonu10m" = Humidity; and "fonspds10m" = Wind Speed. The range covered was January 1, 2021 to January 23, 2024.

The loss function in LASSO regression is defined by Equation (1) and is made of two parts: the first is the Ordinary Least Squares (OLS) loss function, which sums the squared discrepancies between the observed and predicted data. The second part is a penalty applied to the sum of the absolute values of the models' coefficients, given as $|a_i|$, for all coefficients indexed from 1 to n. The penalty's intensity is governed by the regularization parameter λ, which is a non-negative value. As λ is increased, the LASSO model is capable of reducing the coefficients of less significant features to zero, which is a form of intrinsic feature selection. The use of this penalty promotes model simplicity and reduces the risk of overfitting, which produces a model that is generally interpretable, even in extreme climatic conditions [12].

$$\text{Loss function} = \text{OLS loss function} + \lambda * \sum_{i=1}^{n} |a_i|. \quad (1)$$

The Random Forest algorithm employs a combination of decision trees to facilitate machine learning tasks through an ensemble approach. Leveraging bagging and the random subspace method, the algorithm is adept at performing classification, regression, and clustering. The core concept involves constructing numerous decision trees—each tree potentially weak when isolated, but collectively forming a robust classifier or regressor.

In practice, the algorithm initiates by generating a series of bootstrap samples from the original dataset to train individual trees. Subsequently, it builds each tree by selecting a random subset of features at each node, using a specified criterion to identify the optimal feature split. The construction of trees continues until a predefined minimum node size or maximum depth is reached, mitigating overfitting and preserving model simplicity.

For a given input, the final output of the algorithm is derived through an averaging process across all trees for regression, or by majority voting for classification. This technique ensures that the influence of any single, potentially overfitted tree is diluted, enhancing the generalizability and accuracy of the model.

As shown in the flow diagram in fig. 1, the research incorporates Feature Importance, SHAP, and LIME to explain the LASSO-RFR model predictions. These XAI tools help demonstrate the model's transparency and clarify the impact of input features on the predicted output of PV power generation. This is useful feedback which can be used in improving the model's performance, trust and wider implementation of high-performing black-box models.

Indicators of measurement used to assess the models' effectiveness

The evaluation metrics used are the Mean Square Error (MSE) and the Coefficient of determination (R^2), as shown in equations (2) and (3) below:

Mean Square Error (MSE):

$$MSE = \frac{1}{M} \sum_{i=1}^{M} (A - B)^2 \left(Wh/m^2 \right) \quad (2)$$

Where M is the total number of data points, i indicates each data point, A is the predicted values; B is the actual values and Wh/m^2 is the unit of MSE.

R-Squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{M} \left(A - B_{avg} \right)^2}{\sum_{i=1}^{M} \left(B - B_{avg} \right)^2} \tag{3}$$

Where A represents the predicted values of the dependent variable, B represents the actual values of the dependent variable and B_{avg} represents the mean of the actual values of the dependent variable.

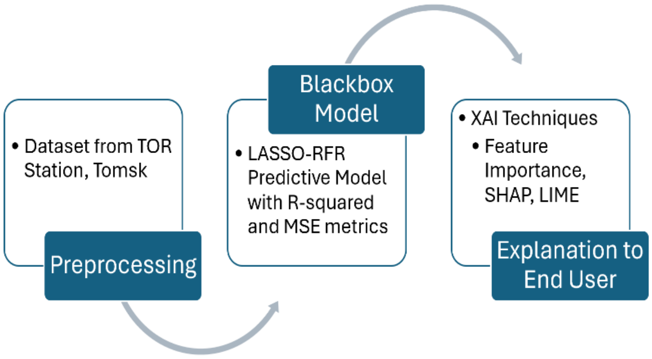


Fig. 1. Flow diagram of the LASSO-RFR-XAI approach

Results

The results presented in this paper seek to demonstrate the transparency and explainability of an AI model (hybrid). XAI techniques such as Feature Importance, SHapley Additive exPlanation (SHAP) and Local Interpretable Model-agnostic Explanation (LIME) are used in explaining the LASSO-RFR model for PV power forecasting. A LASSO-RFR hybrid model is developed where all parameters of the weather conditions in Siberia were featured together with temporal features as input variables for predicted output of generated PV power. The hybrid model has been shown to outperform LASSO-only models. However, the blackbox nature of RFR models require transparency for legal purposes and wider implementation, including integration in smart grids [2][13].

ML Hybrid Model

In this model, available features from the TOR Station that characterize the climatic condition of Siberia were analyzed using the LASSO-RFR method. In using LASSO as a feature selection tool, relatively insignificant parameters can be forced to a coefficient value of zero when the tuning parameter is sufficiently large. This can be seen in fig. 2 where the chart shows that temperature, humidity and windspeed and month are the important parameters with non-zero coefficient. To accurately make a forecast, a predictive model is built by training an RFR model using the selected features from LASSO.

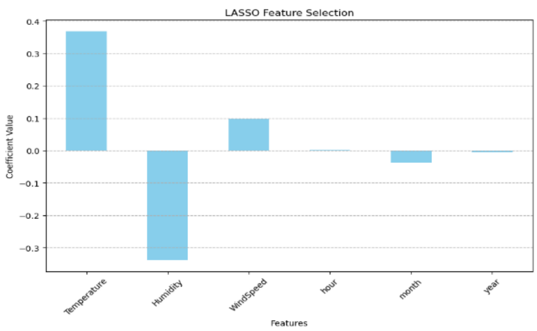


Fig. 2. Plot of LASSO model (normalised data)

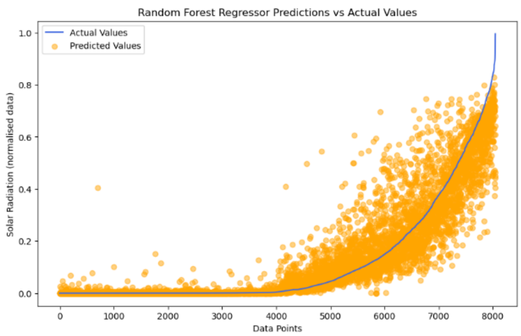
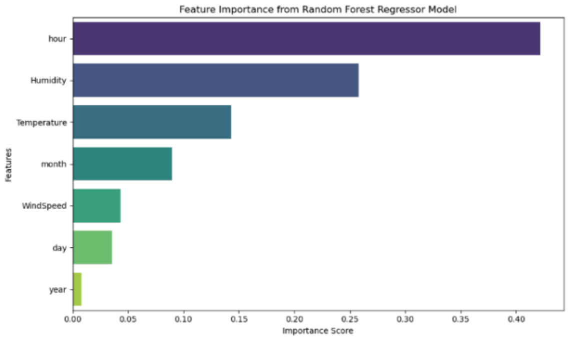


Fig. 3. RFR predictions vs actual values

Fig. 3's RFR performance plot shows true solar radiation values (blue line) closely mirrored by RFR's predictions (orange dots), demonstrating model accuracy. With an R-squared score of 0.859, the model explains 85.9 % of the variance, outperforming the LASSO model, and has a low mean squared error of 0.00584, indicating high accuracy. However, it struggles to capture peak solar radiation, evident from the deviation of predicted from true values at peaks.

XAI Tools

In explaining how AI models make decisions, a feature importance from Random Forest Regressor model. Fig. 4 shows the importance of several features with the hour feature being the most important and the year feature the least important.



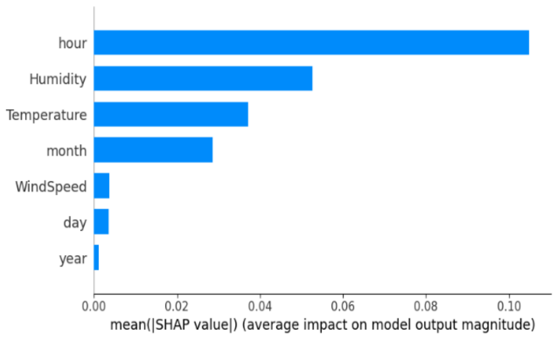


Fig. 4. Feature importance plot of RFR model.   Fig. 5. SHAP plot of RFR model

This fig. 4 is compared with a SHAP impact plot in fig. 5 showing the sensitivity of each input feature on the hybrid model. Again it is seen that the hour feature has the most impact, whilst the year feature has the least impact on the hybrid model. Other features are in the same order in both models.

For redundancy, accuracy, and specificity of the direction of impact, a second XAI model, LIME is used to explain the hybrid model. For LIME, a plot representation with sensitive directions to indicate parameters that increase or decrease the predicted output value of the model and conditions for which the impact is true. In fig. 6 the red bars are to the left of the x-axis and indicate the direction of the impact on the model; that is to decrease the value of the predicted output, while the green bars are to the positive of x-axis, indicating to increase the value predicted output. The length of the bars indicates the importance of the features to the model. Once more the order of importance of the features in LIME is as shown by Random Forest Regression and SHAP. The hour feature at 0.26 or below would negatively impact the model the most. The temperature feature above 0.74 would impact the model positively in the order from “hour” to “year”, which impacts the model the least albeit negatively within the range 0 to or equal to 0.33.

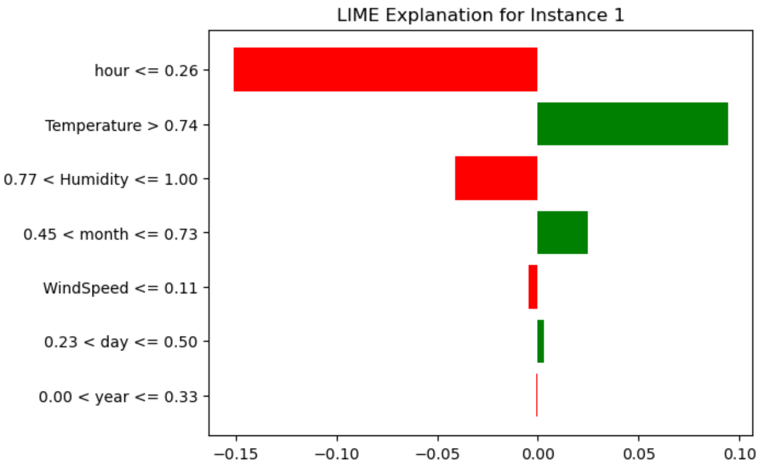


Fig. 6. LIME plot of the RFR model

Conclusion

In concluding, this paper has successfully demonstrated the efficacy of the LASSO-RFR hybrid model for predicting photovoltaic power generation in extreme climatic conditions. By harnessing the transparency and interpretability afforded by XAI techniques such as LIME and SHAP, we have illuminated the varying significance of features contributing to the model's predictions.

The hybrid model, using a nuanced combination of LASSO regression for feature selection and RFR for capturing complex data relationships, outstripped the performance of single-model approaches. The XAI tools provided valuable insights into feature importance and the direction of their impact on predictions, enabling a more nuanced understanding of model behavior. Specifically, the hour of the day emerged as the most influential feature, while other climatic factors also played pivotal roles in forecasting accuracy.

Our findings underscore the potential for integrating XAI tools into smart grid applications, enhancing user trust and model reliability. Such tools pave the way for more nuanced, human-centered AI applications in renewable energy systems. Ultimately, this work contributes to the burgeoning field of XAI, laying the groundwork for future research aimed at refining predictive models and fostering the adoption of AI in critical sectors.

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