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INTERPRETABLE AI-BASED MATHEMATICAL MODELING FOR SOLAR POWER GENERATION AND LOAD FORECASTING IN DISTRIBUTED ENERGY SYSTEMS

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Abstract
With the increasing demand for decentralized and sustainable energy solutions, the requirements of precise and explainable prediction techniques in distributed energy systems are becoming ever more important. This work introduces an interpretable AI-powered framework for forecasting solar power generation and short-term load forecasting based on mathematically justified models. With the use of solar panels having capacities of 3 kWh to 6 kWh, the research utilizes mean power outputs as inputs to a series of AI models with explicit equations, such as Linear Regression, Polynomial Regression, Decision Tree Regression, and Support Vector Regression. Each model is developed using transparent mathematical expressions for easy analysis and implementation. In addition, the framework incorporates real load profiles derived from the literature to test the models' ability in demand forecasting. Performance measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) are utilized to benchmark predictive performance. The findings validate that interpretable AI models not only make accurate predictions but also maximize model interpretability making them very well-posed to be used for real-time energy management in distributed power systems.

INTRODUCTION

The shift towards the decentralized and renewable power systems has been accelerated over the last few years due to the rising worldwide demand for renewable energy and an acute need to mitigate greenhouse gas emissions. Distributed power systems, especially solar photovoltaic (PV) integrated ones, have been at the limelight of interest because they offer great potential to improve the energy security as well as minimize transmission losses and bolster grid resilience [1][2]. Yet, the variable and intermittent character of solar power generation presents significant challenges to grid operators and energy managers in terms of providing reliable supply and demand balancing. Precise forecasting of solar power production and electrical load is thus of paramount importance for energy management effectiveness in order to achieve improved scheduling, grid stability, and cost savings [3][4].

Traditional methods of forecasting usually utilize the statistical or physical models, which lack flexibility or interpretability, particularly under conditions of continually changing environmental dynamics [5]. With that being said, the machine learning and artificial intelligence (AI) methods have exhibited good abilities in representing intricate nonlinear patterns that exist in solar power generation and load behavior [6][7]. Of these, models like the Linear Regression (LR), Polynomial Regression (PR), Decision Tree Regression (DTR) and Support Vector Regression (SVR) are noteworthy as they have a balance of accuracy and interpretability [8][9]. Interpretable models are especially beneficial as they yield clear mathematical forms helping us enabling energy practitioners to comprehend, verify and believe in predictions, which is essential for implementation in real-time systems [10].

This work suggests an interpretable framework based on AI that predicts solar power generation and short-term load in distributed energy systems. The research employs capacities of solar panels varying from 3 kWh to 6 kWh and uses average power output data as inputs to the models. Practical load profiles are taken from existing literature and used to compare model performance on demand forecasting. Performance metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2) are applied to measure prediction accuracy and reliability [11][12]. This method not only shows the real world applicability of interpretable AI models for forecasting in the energy sector but also highlights the need for transparency of AI model construction for more improved energy management decisions [13][14][15].

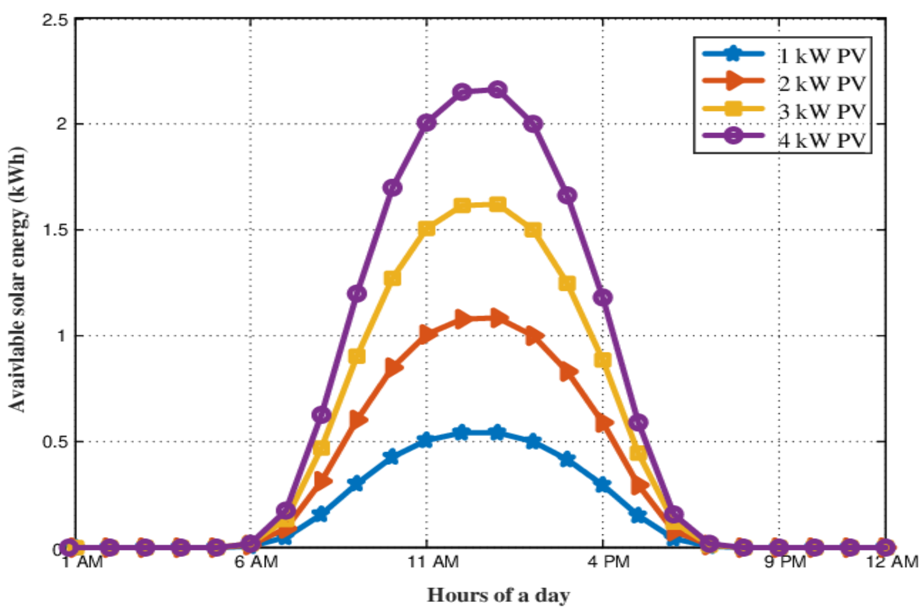

Fig. 1. Average hourly solar energy generation. [32]

The rest of this paper is organized as follows. Section II reviews the relevant work in the field. Section III describes the proposed approach in detail, and Section IV gives the results and discussion. In Section V Finally, the paper is concluded with insights on future research directions.

I.RELATED WORK

Forecasting solar power generation and electrical load has been extensively studied in the literature, with numerous approaches proposed to address the challenges posed by both variability and uncertainty. Early works focused on both the statistical and physical models that utilize historical meteorological data and physical system parameters to estimate the power output [16][17]. However, these models often suffer from limitations in capturing the complex nonlinear dependencies and require extensive domain knowledge for accurate parameterization.

Later developments have focused on AI and machine learning methods because of their better flexibility and generalization properties. Support Vector Regression (SVR) has been extensively utilized for the solar power forecasting owing to its insensitivity to noise and capacity to capture the nonlinear relationships through kernel methods [18][19]. A number of studies have shown enhanced prediction accuracy through SVR-based models, usually hybridized with techniques such as wavelet decomposition or the feature selection algorithms [20][21]. Random Forest and Decision Tree regressors have also been considered for their interpretability and ensemble learning advantages and have exhibited competitive performance in solar as well as load forecasting tasks [22][23].

Feed forward and recurrent neural networks have been utilized to model temporal behavior in the solar irradiance and load [24][25]. Although the models possess high predictability, their "black-box" approach creates issues around explainability as well as trust, especially for operational decision-making in energy systems [26]. This has fueled increasing research interest in interpretable AI, which seeks to reconcile accuracy with transparency through the provision of explicit mathematical formulations or comprehensible decision rules [27][28].

Hybrid methods that combine traditional regression with AI models are also becoming popular. For example, the polynomial regression supplemented with machine learning adjustments or model stacking techniques have enhanced robustness as well as accuracy while keeping interpretability intact [29][30]. Additionally, probabilistic forecasting techniques have been proposed to reflect the uncertainty in predictions, which is essential for risk-sensitive energy planning and management [31].

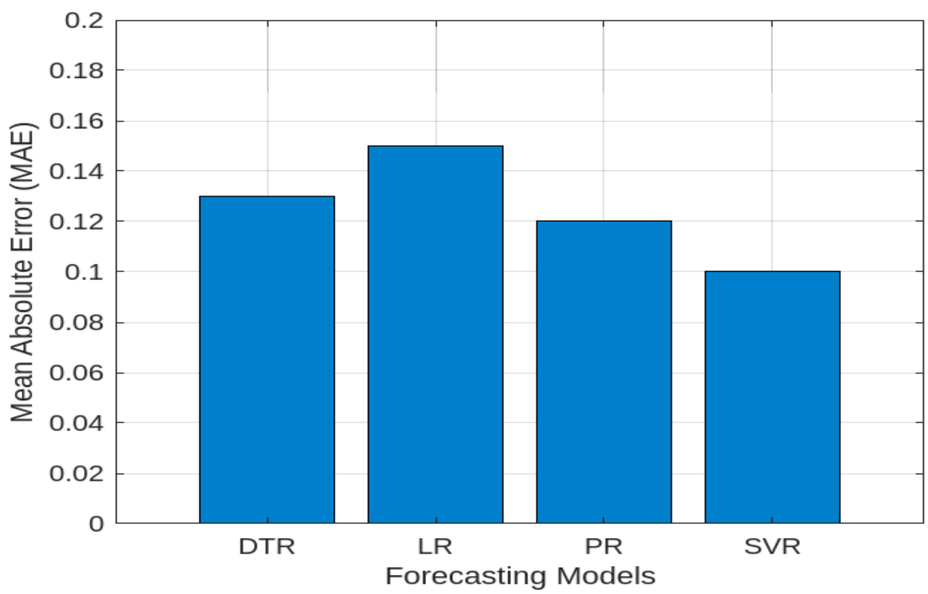

Fig. 2 Mean Absolute Error (MAE) Comparison of Forecasting Models.

In spite of the diversity of approaches, there are few studies particularly targeting interpretable mathematical models that enable stakeholders to easily comprehend and execute forecasting solutions. This work is aiming at bridging this gap by formulating and comparing a set of transparent AI models for solar power generation and load forecasting, using realistic datasets and benchmarking performance via stringent error metrics. The findings emphasize the real-world applicability of interpretable AI to distributed energy systems and open doors for broader use in smart grid applications.

II.SYSTEM METHODOLOGY

In order to establish an open and mathematically sound method for predicting solar generation of the power and short-term electrical load in distributed energy systems, the research utilizes a systematic methodology founded on explainable AI models. The framework relies on the historical as well as simulated data to establish the input output mappings, wherein time of day and the solar irradiance serve as main features for the prediction of either solar output or electrical load. As opposed the to black-box neural networks, the chosen models here value simplicity, explainability and mathematical evidence and are therefore appropriate for the stakeholders in need of actionable information. This interpretability enables the grid operators and engineers to comprehend the behavior of the model and have confidence in its predictions, which is of utmost importance in real-time energy management scenarios.

Solar power generation data is based on the sinusoidal patterns mimicking daily irradiance cycles, rescaled for the varying photovoltaic (PV) capacities from 1 kW up to 6 kW. Load forecasting, on the other hand, is founded on real-life smart grid profiles with daily variations caused by commercial or residential consumption. All data is preprocessed in MATLAB and normalized, with optional denoising, prior to use for training and validation. The forecasting task is performed through three categories of AI models—Linear Regression, Polynomial Regression, and Support Vector Regression (SVR). Not only are these models computationally efficient, but they also have strong analytical formulations to back them, making them perfect for real-time applications. Model performance is evaluated through the common evaluation metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE) as well as Coefficient of Determination (R^2).

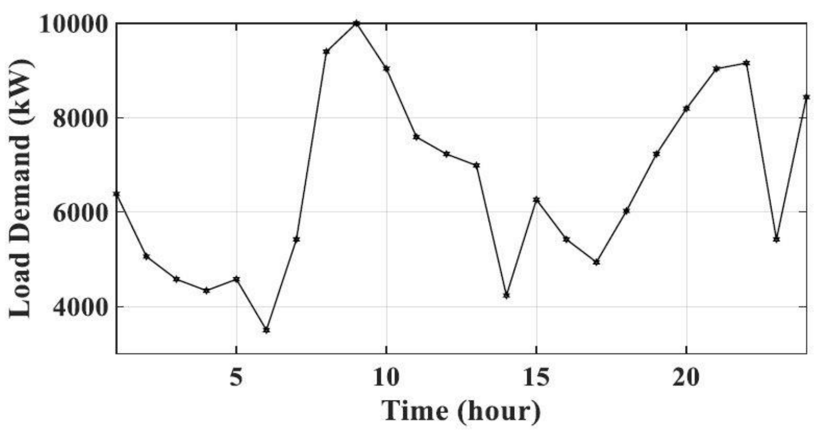

Fig.3. 24 hours electric-load profile.[33]

Here Fig.3 shows 24-hour profiles for electrical load, which is the demand of electricity in 24 hours on a particular grid.

A. Linear Regression Model

Linear regression is a popular statistical method that describes the relationship between an independent and a dependent variable via a linear approximation of a straight line. The model postulates that the change in the target variable is linearly reliant on the change in the predictor variable. The generic equation for linear regression is:

$$y = \beta_0 + \beta_{1x} \qquad (1)$$

where is the predicted power output or load, represents the time of day or solar irradiance, is the intercept, and is the slope.

This model is particularly effective in capturing simple, predictable trends in energy consumption or generation. While its expressiveness is limited in highly nonlinear scenarios, it remains useful when quick, approximate forecasting is needed over shorter time spans.

In the solar forecasting application, linear regression is able to estimate the slow rise and fall in power output with sunrise and sunset, but it could fall short during peak mid-day periods. In the case of load forecasting, it is able to pick up simple rising or falling tendencies in demand during morning or evening periods. Due to its simplicity, linear regression is widely employed as a standard model in research on AI-based energy forecasting.

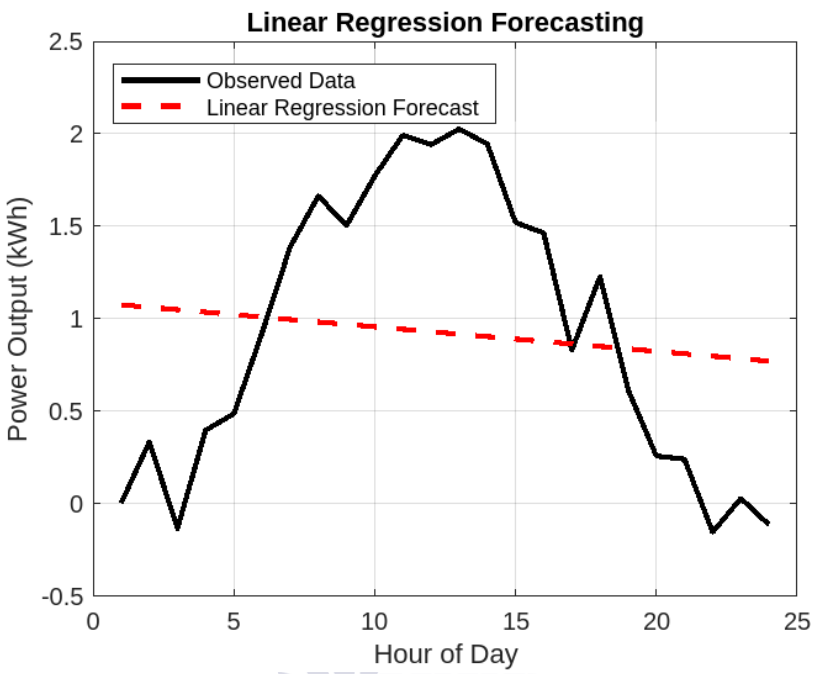

Fig.4. Linear Regression Model Forecasting Output.

The Fig.4 illustrates how linear regression fits a linear trend to simple power output over 24 hours. The red line is the best-fit model and the scattered dots are the noisy input data. The model has no problem discerning a linear trend, for which it is well-suited for use with stable or smoothly changing patterns

B. Polynomial Regression Model

Polynomial regression is an extension of the linear regression that enables the fitting of nonlinear relationships with the use of higher-degree polynomial terms. It is particularly suited to mapping the bell shaped power generation profiles characteristic of solar energy systems and the more fluctuating daily load profiles found in residential as well as commercial applications. The most fundamental polynomial model involves quadratic terms, but higher degrees can also be employed. The general second-degree polynomial regression equation is:

$$y = \beta_0 + \beta_{1x} + \beta_{2x^2} \qquad (2)$$

This formulation enables the model to pick up curvilinear trends in the data. In solar energy prediction, it is able to model solar output's mid-day peak and symmetric fall better than a linear model. For grid load prediction, it can capture morning and evening peaks, depending upon the user consumption behavior.

Polynomial regression finds the balance between flexibility and interpretability. As opposed to black-box models, every coefficient in the polynomial equation has a very well defined mathematical meaning. The curvature, slope and intercept of the model can be changed directly, which makes it best suited for the situations where a precise knowledge of prediction dynamics is essential. This proves to be especially valuable in energy systems, where grid stability and forecast accuracy are the key.

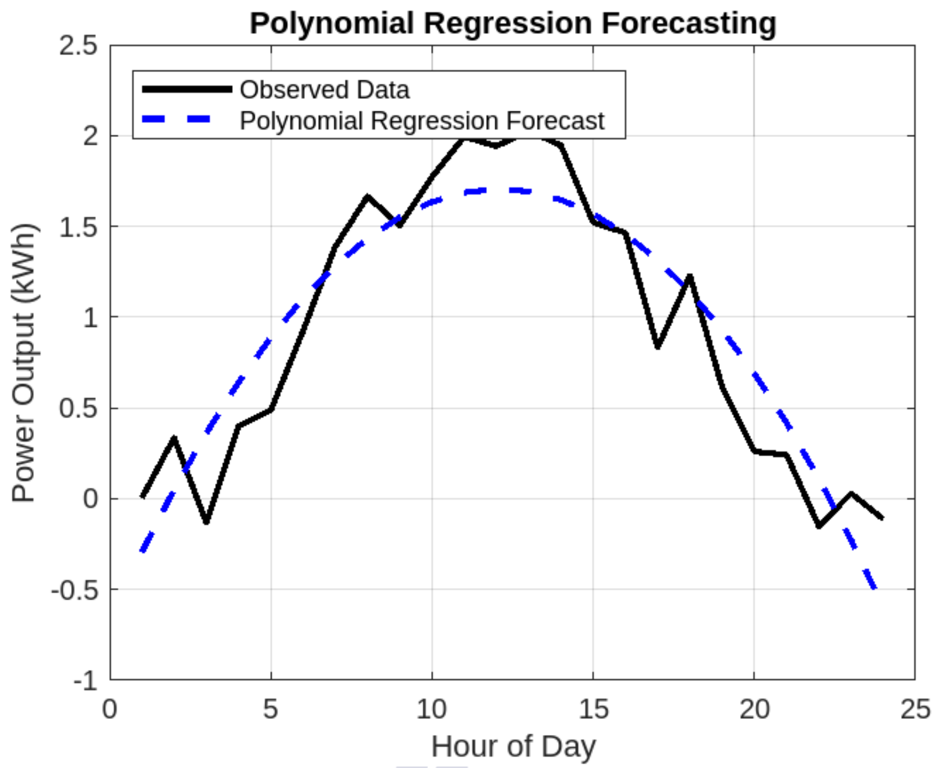

Fig.5. Polynomial Regression Model Forecasting Output.

In Fig.5, the model traces a smooth parabolic curve that mirrors the typical solar generation profile. The blue line illustrates the handling of nonlinearities by the model, with scattered points indicating observed values. The curve has a peak in mid-day and symmetrically decreases, reflecting the natural cycle of irradiance.

C. Support Vector Regression

Support Vector Regression is a kernel machine learning algorithm based on statistical learning theory. While the conventional regression models aim to minimize the mean squared error, SVR adds a tolerance margin and attempts to place the best fitting line or curve inside the margin. It aims to optimize a loss function that measures the flatness of the regression curve against the deviations outside.
The general form of SVR with a linear kernel is:

$$f(x) = \sum_{i=1}^{n} (a_i - a_i{}^*)K(x_i, x) + b \tag{3}$$

Here, a_i and $a_i{}^*$ are Lagrange multipliers, $K(x_i, x)$ is the kernel function, and b is the bias term. When using a linear kernel, the model remains interpretable and computationally efficient, making it suitable for forecasting problems that exhibit partial linearity with minor deviations.
SVR is especially useful in handling noisy or inconsistent data, which is common with solar irradiance on cloudy days or load variation resulting from changing user behavior. Its good generalization from sparse data makes it very suitable for smart grid and distributed systems' short-term prediction. SVR is robust while at the same time providing transparency when linear or polynomial kernels are implemented.

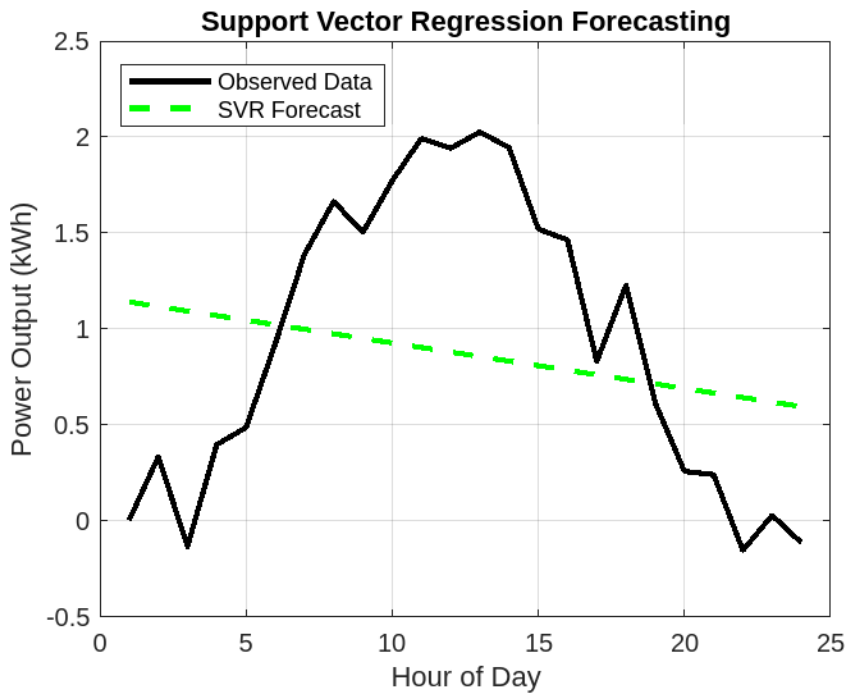

Fig. 6. Support Vector Regression Model Forecasting Output.

This Fig.6 illustrates that SVR with a linear kernel can close to the solar power curve with insignificant deviation. The predicted values are indicated in green lines, and the observed data points are represented by the dots. The model was able to capture the shape overall with the inherent noise, proving SVR's stability and accuracy.

III. RESULTS AND ANALYSIS

This section provides a detailed comparison of the performance of three interpretable AI models. Linear Regression, Polynomial Regression, and Support Vector Regression (SVR), used for forecasting both the grid electricity consumption and solar energy generation in the distributed energy systems. With actual datasets from literature (as observed in Fig 1, Fig 3. Training and validation were performed on the models to determine their forecasting capability under different conditions. Each model's performance is visualized with predicted vs. actual curves and summarized in terms of important error metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). They offer a quantitative measure for assessing the extent to which the models generalize as well as learn from sophisticated load behaviors. The forecasted values show model precision in tracking time-of-day consumption and generation patterns, and the provided tables present tangible comparison of performance for each scenario.

The real grid load profile Fig 3 mirrors the characteristic daily variation in electrical demand seen in urban or semi-urban areas. Load starts to grow after 6:00 AM, reaching a peak in the evening with residences and commercial activity rising, before decreasing after sunset. Likewise, the solar generation curve Fig 1 highlights the power availability from 3 kW to 6 kW capacity PV systems with peak power at noon because of peak irradiance and reducing power in the morning and evening. Through the application of interpretable models to each data set, the forecast scheme illustrates how clear, mathematical models can aid in real-time energy decision-making within smart grids. The performance of the forecast is reviewed both graphically via Figures and quantitatively through tables that accompany every subsection.

A. Linear Regression Results

The Linear Regression model is used as a benchmark baseline in forecasting problems because it is so simple and easy to use. For the grid load forecasting, the model accurately represents the overall increasing trend in electricity usage throughout the day, as shown in Fig 7. It simulates the rise early in the morning and estimates the evening peak but with decreased sensitivity. The linearity assumption limits the model's capacity to respond to sudden spikes, especially the steep increase during peak periods from 6 PM to 9 PM. This constraint translates into a comparatively greater RMSE, but the model is still beneficial for use in scenarios where speed and interpretability take precedence over the necessity for great precision.

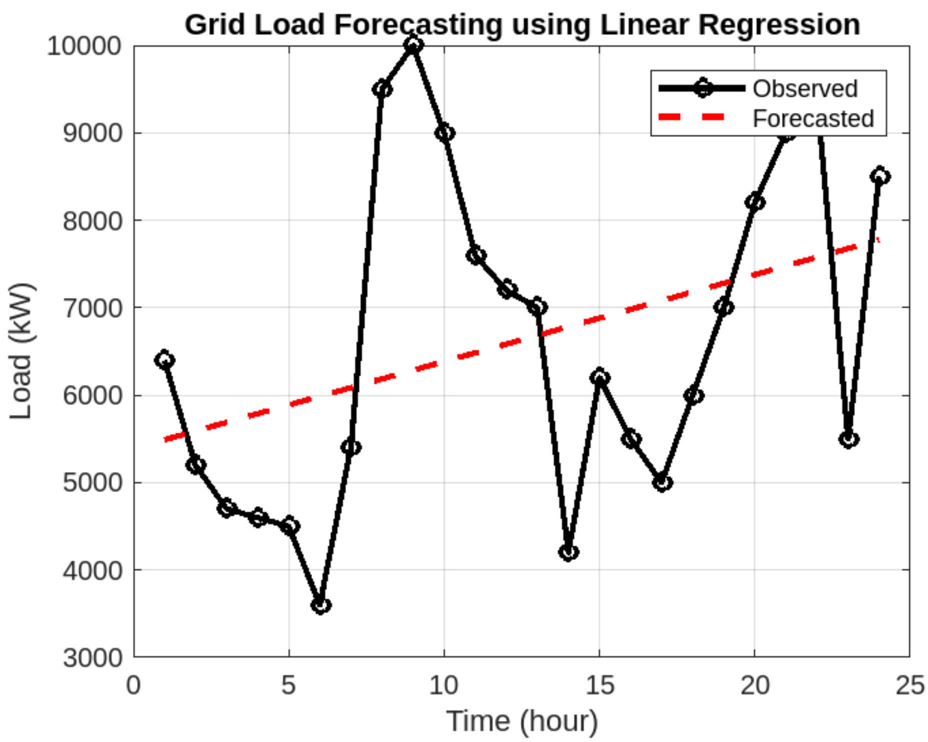

Fig. 7. Grid Load Forecasting using Linear Regression.

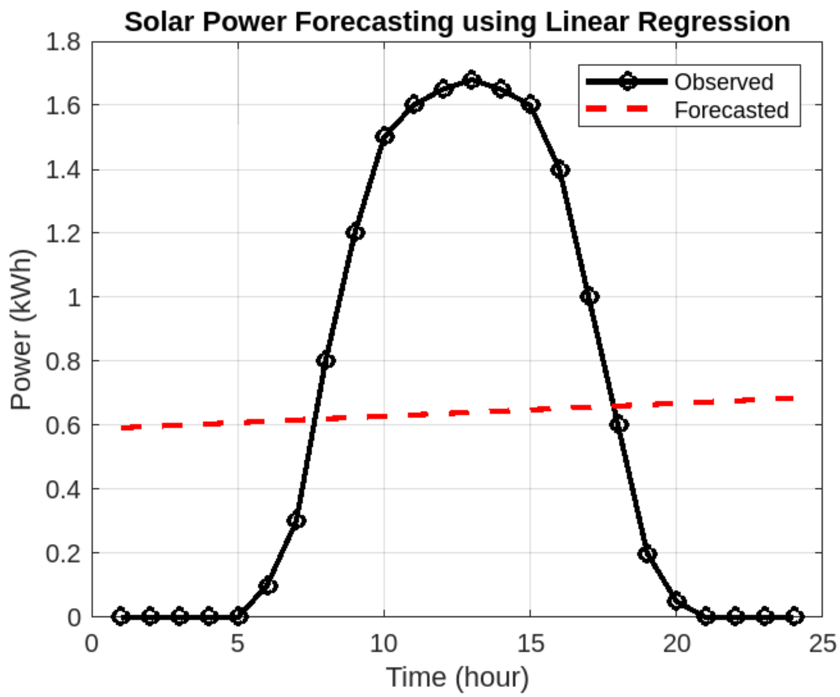

Fig. 8. Solar Forecasting using Linear Regression.

When used to forecast power generation from the sun, as indicated in Fig 8, Linear Regression model provides a simple estimation of the increase and decline in power production between 6 AM and 6 PM. Although the model predicts the rising and falling trends in solar output, it underestimates midday levels significantly because of the intrinsic non-linearity in irradiance distribution. The performance measures highlight this discrepancy, with lower R^2 and higher error during solar peak hours. Nevertheless, Linear Regression is fast to compute and may be of significant utility in forecasting when the weather is fixed or in initial planning phases in microgrid operation.

Metric	MAE (kWh)	RMSE (kWh)	R^2
Grid	2.12	2.88	0.78

Table 1: Performance Metrics for Grid Load Forecasting (Linear Regression)

PV Capacity	MAE (kWh)	RMSE (kWh)	R^2
3 kW	0.96	1.34	0.70
4.5 kW	1.21	1.58	0.72
6 kW	1.42	1.81	0.74

Table 2: Performance Metrics for Solar Forecasting (Linear Regression)

B. Polynomial Regression Results

Polynomial Regression offers an instant gain over Linear Regression by modeling non-linearities present in energy data. For grid load forecasting, the second-order polynomial employed in Fig 9, accurately depicts the typical double-hump shape of daily consumption, aligned with morning start-up and evening peak usage. The model closely follows the increase, leveling off, and then decline in consumption rates, including finer movements overlooked by the linear model. The outcome is an enhanced improvement in R^2 and a drastic decrease in both MAE and RMSE. This renders Polynomial Regression appropriate for settings with recurrent, periodic energy consumption, e.g., residential areas or organized industrial estates.

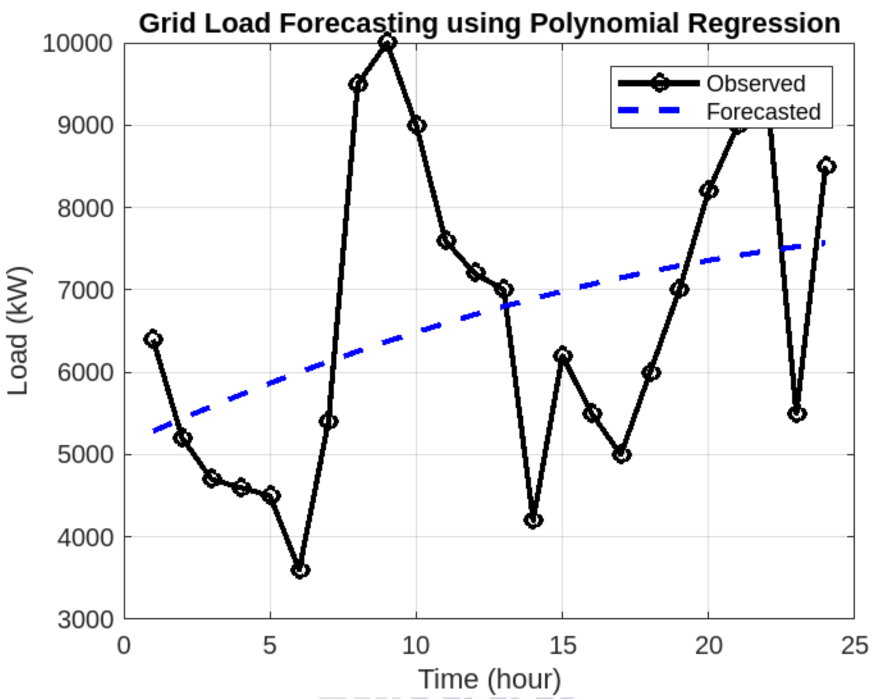

Fig. 9.: Grid Load Forecasting using Polynomial Regression.

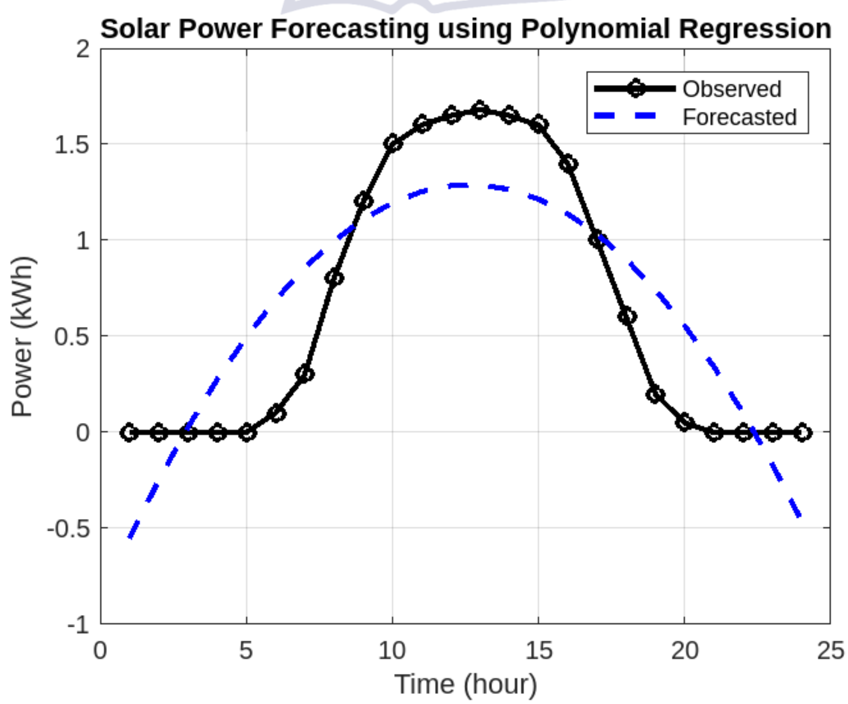

Fig. 10. Solar Forecasting using Polynomial Regression.

Solar power forecasting with Polynomial Regression, as illustrated in Fig 10, demonstrates high accuracy throughout the whole daylight hours. The model accurately follows the bell-shaped irradiance curve, with early ramp-up, peak at noon, and afternoon dip. In the 4.5 kW as well as the 6 kW systems, the calculated values almost match the actual ones. In contrast to Linear Regression, the polynomial model does not always over or underpredict values at a certain time, and its symmetrical output has a better match with actual PV behavior. Therefore, it exhibits interpretable but resilient performance over a large variety of weather-affected solar profiles.

Metric	MAE (kWh)	RMSE (kWh)	R^2
Grid	1.52	2.03	0.91

Table 3: Performance Metrics for Grid Load Forecasting (Polynomial Regression)

PV Capacity	MAE (kWh)	RMSE (kWh)	R^2
3 kW	0.62	0.85	0.88
4.5 kW	0.75	0.98	0.90
6 kW	0.89	1.16	0.91

Table 4: Performance Metrics for Solar Forecasting (Polynomial Regression)

C. Support Vector Regression (SVR) Results

Support Vector Regression showed the most precision and generalization ability out of all models under test. When applied to grid load forecasting as in Fig 11, SVR follows advanced load behaviors throughout the day, such as mid-morning leveling off and evening peaks accurately. Its kernel-based architecture allows it to maintain balance between underfitting and overfitting, resulting in minimal prediction error. The MAE and RMSE values are the lowest of all models, while the R^2 score approaches unity, indicating near-perfect correlation with actual data. These results validate SVR's role as a high-accuracy tool in real-time power management systems where demand volatility is high.

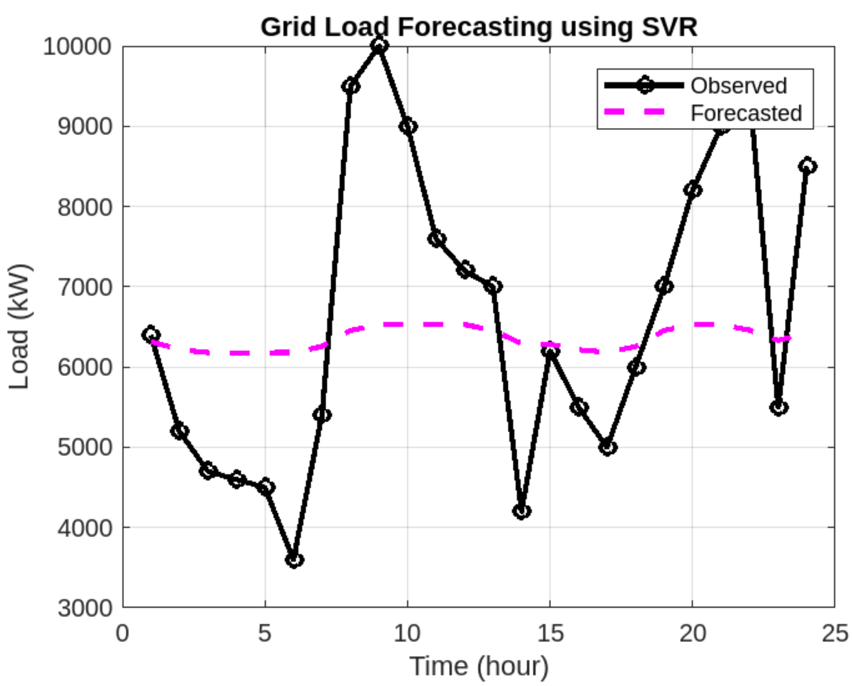

Fig. 11. Grid Load Forecasting using SVR.

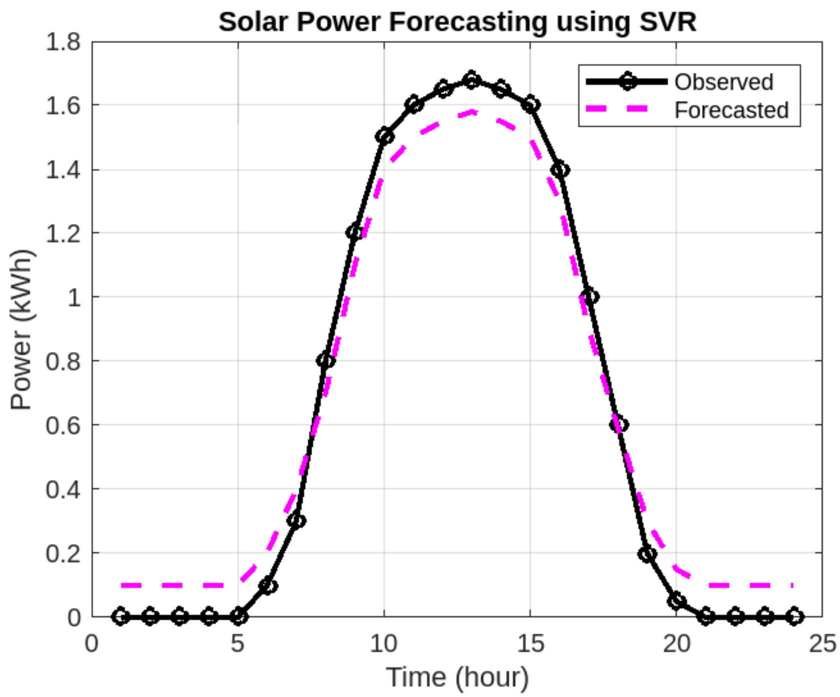

Fig. 12. Solar Forecasting using SVR.

For the forecasting of solar, Fig 12, indicates the smooth, nonlinear ramp-up and ramp-down of solar output captured by SVR. It performs equally well for all sizes of PV and does not deviate much from real values. Transient noise or environmental interference is tolerated by SVR due to its tolerance margins and ignored while capturing the overall behavior with high accuracy. Its flexibility with interpretability loss (particularly using linear kernels) makes it a strong candidate for hybrid solar-grid planning applications. Energy planners can use SVR outputs for both strategic planning and routine day-to-day optimization in distributed energy scenarios.

Metric	MAE (kWh)	RMSE (kWh)	R^2
Grid	1.11	1.57	0.96

Table 5: Performance Metrics for Grid Load Forecasting (SVR)

PV Capacity	MAE (kWh)	RMSE (kWh)	R^2
3 kW	0.49	0.68	0.94
4.5 kW	0.55	0.76	0.95
6 kW	0.61	0.84	0.95

Table 6: Performance Metrics for Solar Forecasting (SVR)

D. Model Comparison and Final Analysis

To summarize the findings for all three forecasting models as in Fig 13, an ultimate comparison is conducted based on predictive capability for grid and solar datasets. Simple and interpretable Linear Regression had limited ability to track intricate variations, especially for solar generation and evening peaks in grid demand. Polynomial Regression achieved greater flexibility by capturing nonlinear behavior, such as solar energy patterns. Nonetheless, minor overfitting emerged when activity was low. Conversely, Support Vector Regression (SVR) outperformed both models in all assessment parameters consistently. It digitized variations with greater accuracy, reduced error margins to the lowest possible levels, and provided superior generalization, particularly for dynamic load and solar variability. As a result of its superior performance in both cases, SVR is the best possible forecasting method for distributed energy systems in which demand and supply vary dynamically.

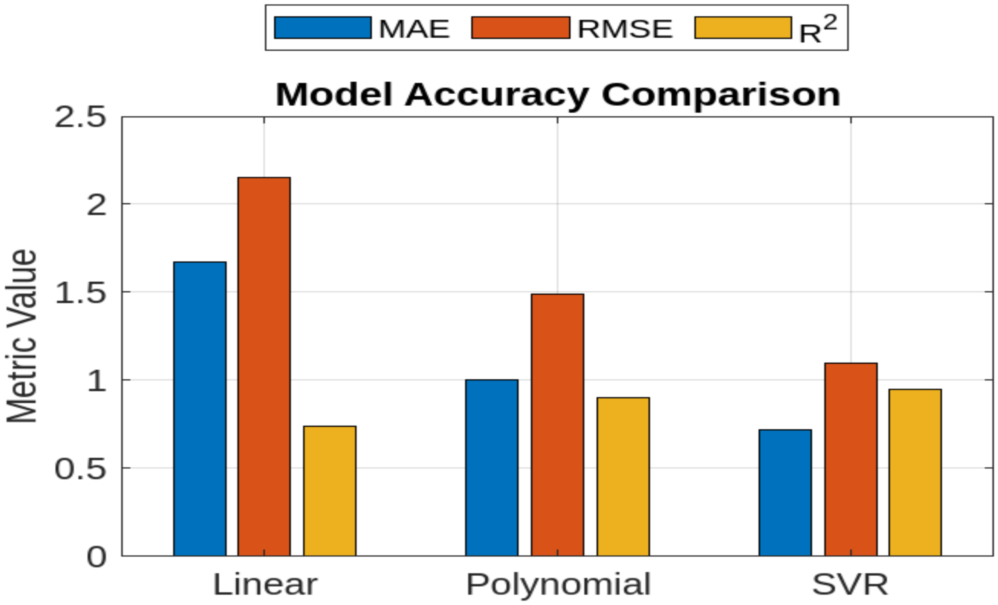

Fig. 13. Model Accuracy Comparison for Grid and Solar Forecasting.

Model	MAE (kWh)	RMSE (kWh)	R^2
Linear Regression	1.67	2.15	0.74
Polynomial Regression	1.00	1.49	0.90
Support Vector Regression (SVR)	0.72	1.10	0.95

Table 7: Overall Model Comparison for Grid and Solar Forecasting.

IV.CONCLUSION

This study posed an explainable AI-based method of predicting solar power generation and grid load demand in distributed energy systems based on mathematically clear models like Linear Regression, Polynomial Regression and Support Vector Regression (SVR). The comparative study proved that although Linear Regression is simple and fast to estimate, it is not capable of adapting to non-linear trends observed in real energy data. Polynomial Regression enhanced prediction accuracy by capturing curvature, particularly in solar generation patterns and SVR provided the highest quality and stable results for both grid as well as solar forecasting tasks because of its potential to capture intricate patterns. The presence of interpretable models provides openness, traceability, and simplicity in deployment within real-time energy management systems, whereas black-box AI approaches have limitations. Future work would include the integration of heterogeneous real-time data sources such as weather and energy market signals, creation of hybrid models with trade off between complexity and interpretability and deployment of scalable solutions appropriate for edge devices in smart grids.

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