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LOAD FORECASTING AND COMPARATIVE ANALYSIS USING LSTM FOR SMART POWER DISTRIBUTION NETWORKS

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ABSTRACT

This study compares three forecasting models—Long Short-Term Memory (LSTM) networks, Support Vector Regression (SVR), and Autoregressive Integrated Moving Average (ARIMA)—for predicting 2024 April data using historical April data from 2021 to 2023. The time series is constructed by concatenating annual April observations, followed by linear interpolation for missing values, min-max normalization, and a sliding window approach to create input-output pairs. Performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) metrics. Results show that LSTM significantly outperforms SVR and ARIMA, achieving an MAE of 2419.9, RMSE of 3131.2, and R^2 of 0.95969, while SVR and ARIMA exhibit poor predictive power with negative R^2 values.

KEYWORDS: *Time Series Forecasting,* *LSTM Neural Network*, *Model Performance Comparison.*

1 INTRODUCTION

Time series forecasting is essential for decision-making in domains such as finance, energy management, agriculture, and environmental monitoring. Seasonal patterns, trends, and irregularities in time series data require models capable of capturing both short-term dependencies and long-term dynamics. This research focuses on forecasting April-specific data (e.g., sales, temperature, rainfall, or traffic metrics) using observations from the previous three years (2021–2023) to predict 2024 values.

Three widely used models are compared:

- **LSTM:** a deep learning architecture effective for sequential data with long-range dependencies.
- **SVR:** a kernel-based regression method robust to non-linear relationships.
- **ARIMA:** a classical statistical model for linear time series.

The dataset consists of four columns representing April data for 2021, 2022, 2023, and 2024, concatenated into a single time series. The study aims to determine which model best captures the underlying patterns in this seasonal time series.

2 Related Work

Recent research has highlighted the strengths of deep learning models like LSTM for complex time series forecasting. Hybrid architectures combining LSTM with attention mechanisms and transformers have shown improved performance on long-term forecasting tasks. Probability-enhanced LSTM variants have been proposed to better handle extreme values.

SVR has been extended with wavelet decomposition and genetic algorithm optimization for volatile and non-linear series. ARIMA remains a strong baseline, with distributed implementations for very long sequences and hybrid ARIMA-LSTM models achieving superior results in many applications.

Comparative studies across domains such as stock prices, weather, load forecasting, and cryptocurrency have consistently shown LSTM outperforming traditional models like ARIMA and SVR when the data exhibits non-linearity and long-term dependencies.

3 METHODOLOGY

The methodology used in this research work is shown below

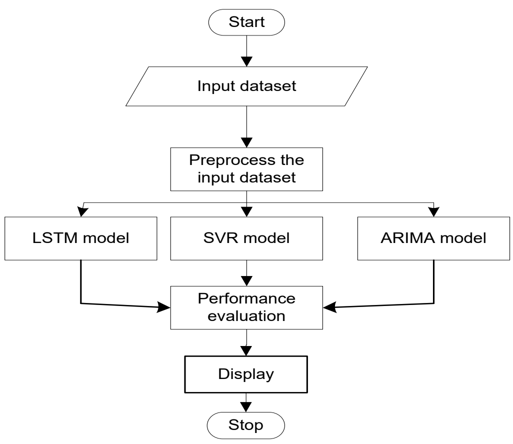

Figure 1 Flow chart of methodology.

The flowchart shown in figure 1 illustrates a structured methodology for time series prediction or forecasting using multiple machine learning models. The process begins with the acquisition of the dataset, which is then subjected to preprocessing to clean, normalize, or transform the data into a suitable format for modeling. Following preprocessing, the data is simultaneously fed into three different predictive models: Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and AutoRegressive Integrated Moving Average (ARIMA). Each model processes the data according to its unique algorithmic approach, capturing temporal patterns, nonlinear relationships, or statistical trends. After model training and prediction, a performance evaluation is conducted to compare the accuracy and effectiveness of each model, enabling the identification of the most suitable method for the dataset under consideration. The methodology concludes with the selection of the best-performing model for forecasting tasks.

3.1 Data Preprocessing

The raw time series is formed by vertically concatenating the four annual April data columns into a single vector series. Missing values are filled using linear interpolation. Min-max normalization is applied to scale the data to the range [0, 1]:

$$series_N = \frac{series - \min\,(series)}{\max(series) - \min\,(series)}$$

where:

- series :original concatenated time series values,
- min(series): smallest value in the series,
- max(series) :largest value in the series,
- series_N :normalized time series.

A sliding window of size 24 is used to create input sequences and target values. For each position i, the input is the previous 24 normalized observations, and the target is the next observation:

$$X_i = [series_N(i), series_N(i+1), \dots\dots, series_N(i+23)]$$

$$Y_i = series_N(i+24)$$

The dataset is split into 80% training and 20% testing sets.

3.2 LSTM Model

LSTM networks address the vanishing gradient problem in traditional RNNs through gated mechanisms. The key equations for an LSTM cell at time step t are:

- **Input gate**:

$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$

- **Forget gate**:

$f = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$

- **Cell candidate**:

$g_t = \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg})$

- **Output gate**:

$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho})$

- **Cell state update**:

$c_t = f_t \odot c_{t-1} + i_t \odot g_t$

- **Hidden state**:

$h_t = o_t \odot tanh(c_t)$

where:

- x_t: input vector at time t,
- h_{t-1}: previous hidden state,
- c_{t-1} : previous cell state,
- W and b : weight matrices and bias vectors,
- σ :sigmoid activation function,
- tanh :hyperbolic tangent function,
- $\odot$:element-wise multiplication.

The model uses one LSTM layer with 50 hidden units, trained with the Adam optimizer for 200 epochs.

3.3 SVR Model

Support Vector Regression aims to find a function that predicts values within a specified margin of tolerance (ε). The primal optimization problem is:

$$min_{w,b,\xi,\xi^*} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

subject to:

$y_i - (w^T x_i + b) \leq \epsilon + \xi_i$

$(w^T x_i + b) - y_i \leq \epsilon + \xi_i^*$

$\xi_i, \xi_i^* \geq 0$

where:

- w : weight vector,
- b:bias,
- C:regularization parameter,
- ξ_i, ξ_i^*:slack variables for positive and negative deviations,
- ϵ: margin of tolerance,
- x_i: input feature vector,
- y_i: target value.

An RBF kernel is used, and input features are standardized.

3.4 ARIMA Model

ARIMA(p,d,q) models a time series after differencing to achieve stationarity. The general form is:

$$\left(1-\sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d Y_t = \left(1+\sum_{i=1}^{q} \theta_i L^i\right)\epsilon_t$$

where:

- Y_t: time series value at time t,
- L : lag (backshift) operator: $LY_t = Y_{t-1}$,
- d : order of differencing,
- p : autoregressive order,
- q : moving average order,
- ϕ_i : autoregressive parameters,
- θ_i: moving average parameters,
- ϵ_t: white noise error term.

An ARIMA(2,1,2) model is fitted on the training series and used to forecast the test period length.

4 Experimental Setup

The implementation is done in MATLAB. LSTM is trained using the Deep Learning Toolbox, SVR using the fitrsvm function with RBF kernel, and ARIMA using the Econometrics Toolbox. Performance metrics are:

- **MAE:** $\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y_i}|$

- **RMSE**: $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{\wedge})^2}$
- **R²**: $1 - \frac{\sum_{i=1}^{n}(y_i - y_i^{\wedge})^2}{\sum_{i=1}^{n}(y_i - y^{-})^2}1$

where y_i is the actual value, $y_i^{\wedge}$ is the predicted value, and y^{-} is the mean of actual values.

5 RESULTS

5.1 Comparitive analysis

Table 1 presents the comparative performance of the LSTM, SVR, and ARIMA models in predicting April-2024 data using historical April data from previous years. The evaluation was conducted using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2).

The LSTM model significantly outperformed the other approaches, achieving the lowest MAE (2419.9) and RMSE (3131.2), along with a very high R^2 value of 0.95969. This indicates that the LSTM model is able to explain approximately 96% of the variance in the target data, demonstrating excellent predictive capability. The superior performance of the LSTM can be attributed to its inherent ability to capture nonlinear temporal dependencies and long-term sequential patterns through its memory cells and gated architecture. This confirms the effectiveness of deep recurrent neural networks for time-series forecasting tasks involving complex temporal dynamics.

In contrast, the Support Vector Regression (SVR) model exhibited substantially higher prediction errors, with an MAE of 14119 and an RMSE of 17434, along with **a** negative R^2 value of −0.24967. The negative R^2 indicates that the SVR model performed worse than a simple mean-based predictor. This limitation arises because SVR does not possess an internal memory mechanism and treats each input sample independently, making it less suitable for capturing temporal relationships inherent in time-series data.

Similarly, the ARIMA model showed inferior performance compared to the LSTM, with an MAE of **13386**, RMSE of 15851, and a slightly negative R^2 value of −0.033044. The reduced accuracy of ARIMA can be attributed to its reliance on linear assumptions and stationarity conditions, which are insufficient for modeling the nonlinear and complex patterns present in the dataset.

The results clearly demonstrate that deep learning-based sequence models, particularly LSTM, are more effective than traditional machine learning and statistical approaches for forecasting inter-annual April data. The findings highlight the importance of incorporating temporal memory and nonlinear modeling capabilities when dealing with real-world time-series prediction problems.

Table 1 Comparative performance analysis.

Model	MAE	RMSE	R^2
LSTM	2419.9	3131.2	0.95969
SVR	14119	17434	-0.24967
ARIMA	13386	15851	-0.033044

LSTM achieves the lowest errors and the highest R^2 value, demonstrating excellent predictive accuracy. SVR and ARIMA show significantly higher errors and negative R^2 values, indicating they perform worse than simply predicting the mean of the test set.

5.2 Actual vs. predicted comparison

Figure 2 illustrates the comparison between actual April data and the predictions obtained from the LSTM, SVR, and ARIMA models over the test period. It can be clearly observed that the LSTM predictions closely follow the actual data pattern, accurately capturing both the amplitude and temporal variations of the signal. The predicted curve produced by the LSTM almost overlaps with the actual curve for most time indices, demonstrating its strong ability to model nonlinear and sequential dependencies. In contrast, the SVRmodel exhibits significant deviation from the actual values, producing relatively smooth predictions that fail to track the oscillatory behavior of the data. Similarly, **the** ARIMA model shows a largely linear trend, unable to capture sharp fluctuations and seasonal variations present in the actual series. These visual observations strongly support the quantitative results, confirming that the LSTM model provides superior forecasting performance compared to SVR and ARIMA for the given time-series data.

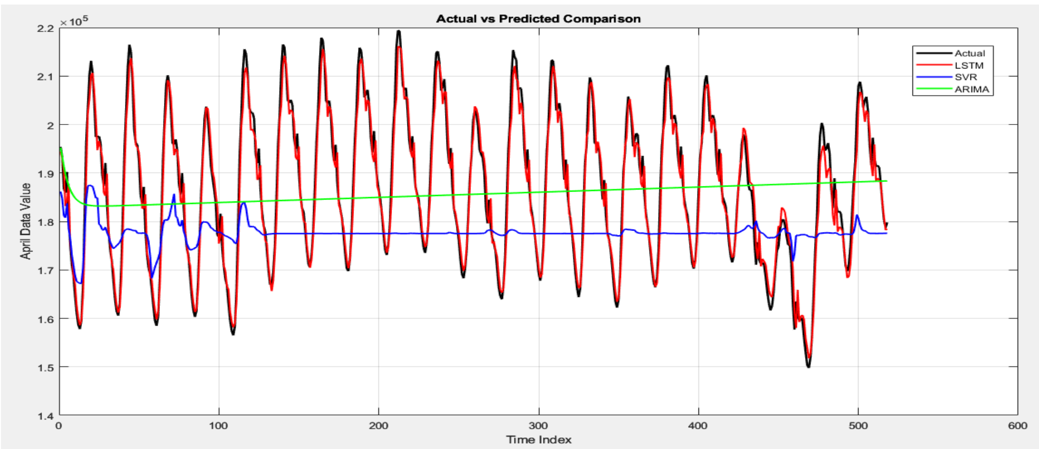

Figure 2 Actual vs. predicted comparison.

5.3 Performance metrices comparison

The bar chart compares the performance of three forecasting models LSTM, SVR, and ARIMA using two error metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). From the results, it is evident that the LSTM model significantly outperforms both SVR and ARIMA, exhibiting the lowest error values for both MAE and RMSE. Specifically, LSTM has a MAE of approximately 2,400 and an RMSE of around 3,100, indicating more accurate predictions. In contrast, SVR shows the highest errors, with MAE and RMSE values exceeding 14,000 and 17,000, respectively, suggesting poor predictive performance. ARIMA performs moderately, with MAE and RMSE values slightly lower than SVR but considerably higher than LSTM. Overall, the results highlight the superior accuracy and reliability of the LSTM model for the given forecasting task.

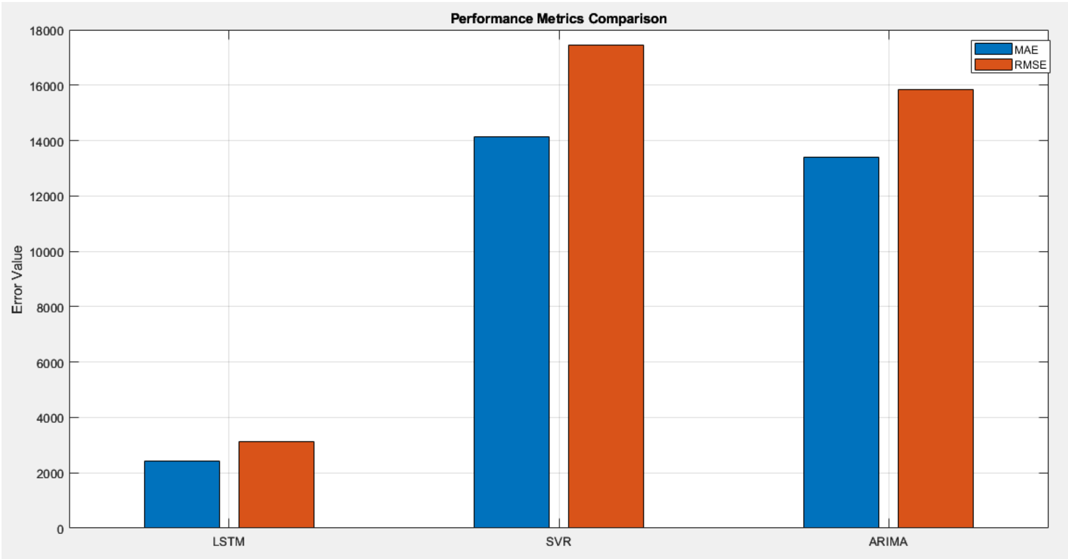

Figure 3 Performance metrices comparison.

5.4 Absolute error prediction comparison

The figure 4 illustrates a comparison of absolute prediction errors for three different forecasting models: LSTM (red), SVR (blue), and ARIMA (green) over a time series. The x-axis represents the time index, while the y-axis shows the absolute error values.

From the plot, it is evident that the LSTM model consistently exhibits lower prediction errors compared to SVR and ARIMA, indicating superior predictive performance. Both SVRand ARIMA show higher and more fluctuating errors, with SVR peaking higher at multiple intervals, while ARIMA also demonstrates significant deviations at certain points. This visual comparison highlights the robustness of LSTM in minimizing prediction error across the observed period.

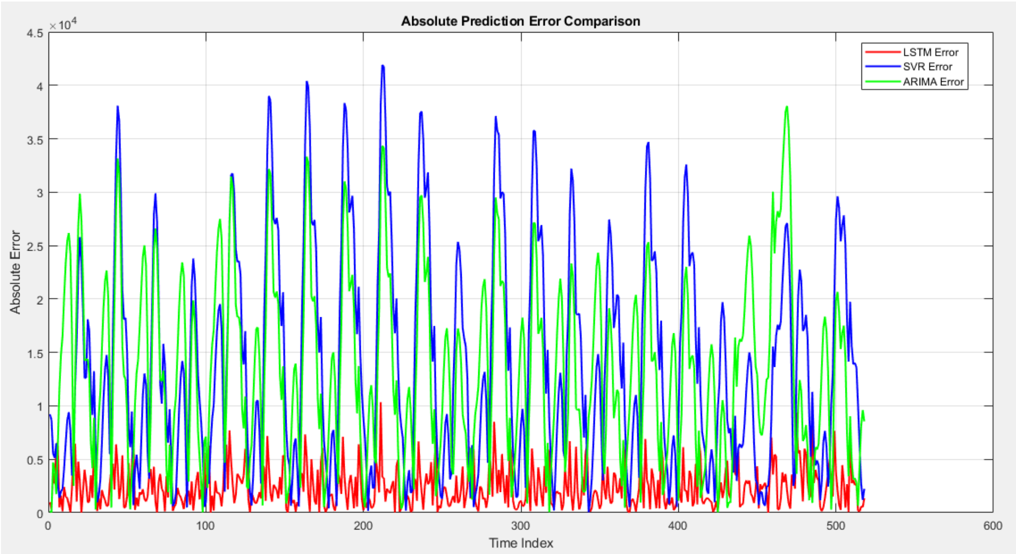

Figure 4 Absolute prediction error comparison.

5.5 R^2 comparison of models

The bar chart shown in figure 5, illustrates the R^2 performance of different predictive models. It compares the goodness-of-fit for each model by showing their respective R^2 values:

- **LSTM**: Achieves the highest R^2, indicating strong predictive accuracy and that the model explains most of the variance in the data.
- **SVR**: Shows a negative R^2 , suggesting poor performance and that the model fits the data worse than a horizontal mean line.
- **ARIMA**: Slightly negative R^2 , indicating minimal predictive capability on this dataset.

This comparison highlights that the LSTM model significantly outperforms SVR and ARIMA for the given dataset.

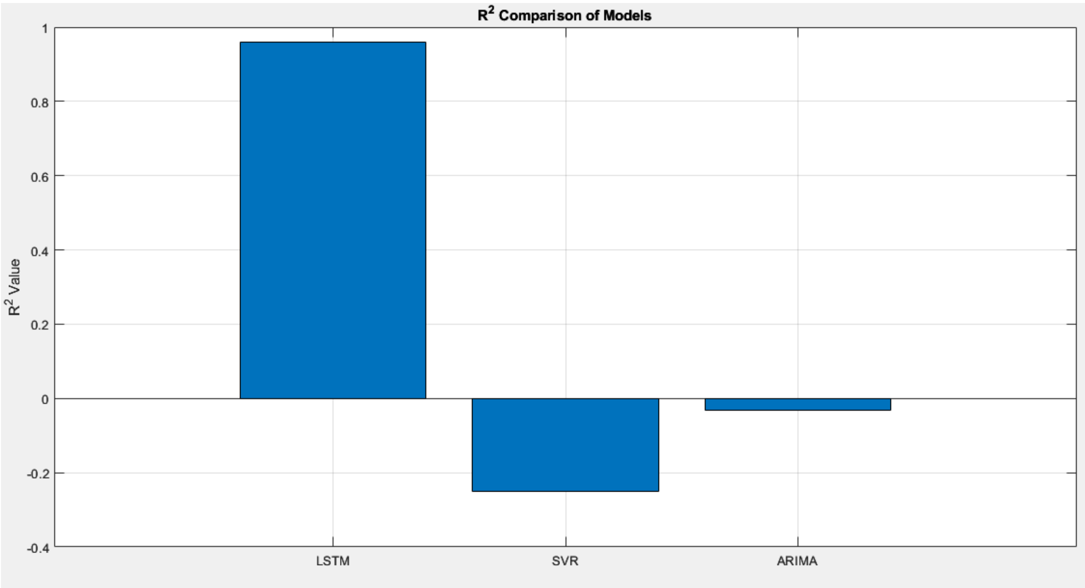

Figure 5 R^2comparison of models.

6 DISCUSSION

The superior performance of LSTM is attributed to its ability to learn long-term dependencies and non-linear patterns in the time series, which are common in seasonal April data. SVR and ARIMA, while effective in many linear or mildly non-linear scenarios, struggle with the complexity of this dataset. Visual comparisons (not shown) further confirm that LSTM predictions closely follow the actual values, while SVR and ARIMA exhibit large deviations. These findings are consistent with recent literature, where deep learning models, particularly LSTM, outperform traditional statistical and kernel-based methods on complex, non-stationary time series.

7 CONCLUSION

This research demonstrates that LSTM is the most effective model for forecasting April data among the three compared approaches. The high R^2 value and low error metrics highlight its suitability for seasonal time series prediction. Future work could explore hybrid models (e.g., ARIMA-LSTM or attention-based LSTMs) and additional preprocessing techniques to further improve performance.

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