Predictive Analysis of Energy Demand Prediction using Deep Learning Approach

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Abstract-Energy demand prediction is crucial for efficient resource management and planning in rapidly urbanizing cities like Bangalore. This study explores a deep learning-based predictive analysis approach using time-series energy consumption data provided by BESCOM. The study explores and evaluates various models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for predicting quarterly energy demand. Key metrics such as RMSE, MAE, and MAPE are used to evaluate predictive accuracy, while qualitative metrics assess the robustness and interpretability of the models. Results demonstrate that hybrid and tailored architectures outperform traditional models, offering improved accuracy and scalability.

1. INTRODUCTION

Predictive analysis has become one of the most transformative methodologies in modern times, with its roots dating back to the early 20th century. Initially relying on statistical techniques like regression analysis and time-series forecasting, these methods aimed to analyze historical data to predict future outcomes. Early applications included fields such as agriculture and economics, where accurate predictions of crop yields and economic trends were critical. However, these methods were constrained by limited computational resources and data availability, often yielding simplistic results with significant manual effort.

These innovations expanded the scope of predictive analysis to address complex problems like customer segmentation, fraud detection, and early artificial intelligence applications, enabling organizations to use data strategically for competitive advantages and improved efficiency.

Energy demand forecasting, a critical component of energy management, ensures the efficient operation of modern energy systems. Accurate forecasts help energy providers maintain grid stability, optimize resource allocation, and reduce operational costs.Short-term forecasts support real-time grid management, load balancing, and renewable energy integration. Medium-term forecasts aid in maintenance scheduling, procurement, and demand-side management, while long-term forecasts guide infrastructure investments, policy decisions, and the transition to cleaner energy systems.

Deep learning (DL) has become a groundbreaking approach, with models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) demonstrating exceptional capability in handling time-series data and uncovering intricate patterns. These models play a crucial role in improving the precision and dependability of energy demand predictions, effectively tackling the complexities of contemporary energy systems.

2. LITERATURE REVIEW

Energy demand forecasting has seen significant progress with the adoption of deep learning (DL) techniques, which provide advanced capabilities to analyze complex and dynamic energy consumption patterns. Advanced architectures, including Long Short-Term Memory (LSTM) units and Gated Recurrent Units (GRUs), have addressed issues like vanishing gradients, allowing for improved management of long-term dependencies and intricate time-series data shaped by factors such as weather variations and consumer behavior.CNNs, on the other hand, excel in extracting spatial features, making them ideal for integrating environmental and geographical data, such as solar irradiation and wind patterns, into energy forecasting models. Recent advancements like 3D CNNs have further improved accuracy in scenarios requiring spatio-temporal analysis, allowing models to process both spatial and temporal dependencies simultaneously. Hybrid models combining the strengths of RNNs and CNNs, such as LSTM-CNN frameworks, provide a comprehensive solution by leveraging temporal insights alongside spatial features, enabling higher prediction accuracy and better adaptability to diverse datasets. A key innovation in DL-based energy forecasting is the integration of attention mechanisms, which improve both model performance and interpretability. These mechanisms allow models to focus on the most relevant inputs, such as peak demand periods, extreme weather events, or critical temporal and spatial features. By dynamically assigning weights to important data points, attention mechanisms enhance the ability to capture subtle but significant patterns, making them particularly effective for applications in renewable energy forecasting, grid stability analysis, and demand-response systems. These advancements collectively enable more precise, reliable, and actionable energy demand predictions, supporting better planning and management of energy systems in an increasingly dynamic environment.

3. PROBLEM STATEMENT

The increasing complexity of modern energy systems presents significant challenges for energy demand forecasting. Factors such as weather variability, seasonal changes, economic activities, and the integration of renewable energy sources introduce substantial non-linearities and temporal dependencies into consumption patterns. Traditional statistical models, though widely used, struggle to capture these intricate relationships, resulting in suboptimal forecasting accuracy and adaptability.

Deep learning (DL) techniques, particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have emerged as promising tools for addressing these challenges. By leveraging their capacity to model temporal and spatial patterns, these techniques can enhance the accuracy and reliability of energy demand predictions. However, issues such as computational efficiency, model interpretability, and data quality continue to hinder large-scale deployment in real-world scenarios.

This study aims to bridge these gaps by developing a deep learning-based predictive framework tailored for urban energy systems, with a focus on improving forecasting accuracy, scalability, and robustness. By addressing the limitations of existing models and incorporating real-time and historical data, this research seeks to contribute to the optimization of energy systems and the achievement of sustainability goals.

4. PROBLEM SOLUTION

The proposed solution is an end-to-end demand forecasting system built using a Recurrent Neural Network (RNN) & Convolutional Neural Network (CNN) to predict future demand patterns based on historical data.

4.1.Recurrent Neural Network (RNN)

The Recurrent Neural Network (RNN) preprocesses historical demand data by normalizing it with MinMaxScaler and structuring it into 30-timestep sequences for supervised learning. The model, consisting of a SimpleRNN layer with 64 units, a Dropout layer, and a dense output layer, is trained on an 80-20 data split for 20 epochs using the Adam optimizer and MSE loss. Metrics like MAE, RMSE, R^2, and MAPE evaluate accuracy, while January 2017 data validates the model through daily average comparisons. Visualizations of actual vs. predicted values demonstrate the RNN's effectiveness in capturing trends, highlighting its robustness and adaptability for time-series forecasting.

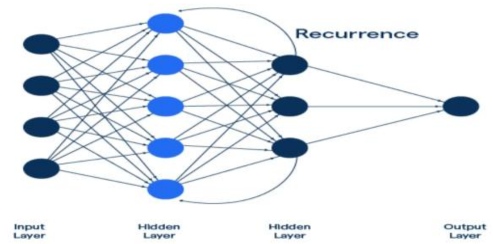

Figure1:Architecture of the RNN Model

Figure 1 illustrates the architecture of a Recurrent Neural Network (RNN) designed for sequential or time-series data processing. It begins with an input layer, where features are fed into the network. The hidden layers, with recurrent connections, retain information from previous time steps, enabling the model to learn temporal patterns. The output layer generates the final prediction, such as a regression value or class label.

4.2. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) processes historical demand data by normalizing it with MinMaxScaler and structuring it into 30-timestep sequences. The data is reshaped into a 3D format, split into 60% training and 40% testing sets, and passed through a CNN architecture with a Conv1D layer (64 filters), a ReLU activation, a Dropout layer, and dense layers for prediction. The model, compiled with the Adam optimizer and MSE loss, is trained for

50 epochs. Performance is evaluated using metrics like MAE, RMSE, R^2, and MAPE. January 2017 data further validates the model through daily average comparisons. Visualizations of actual vs. predicted trends confirm the CNN's effectiveness and reliability in time-series forecasting.

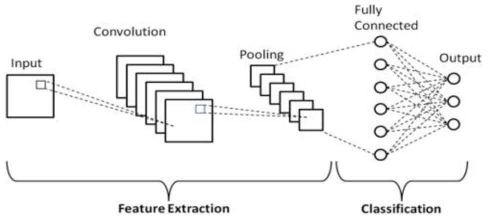

Figure 2:Architecture of CNN algorithm

Figure 2 depicts the architecture of a Convolutional Neural Network (CNN), which comprises two primary stages: feature extraction and classification. The feature extraction stage starts at the input layer, where raw data undergoes processing through convolutional layers to identify patterns such as edges and textures. These patterns are then passed through pooling layers to down sample spatial dimensions while preserving essential features. In the classification stage, the features are flattened and fed into fully connected layers, which map the extracted features to specific outputs. The final layer produces the classification or prediction results, making this structure highly efficient for tasks such as image recognition and classification.

5. METHODS RESULTS AND DISCUSSION

5.1. Recurrent Neural Network (RNN) results

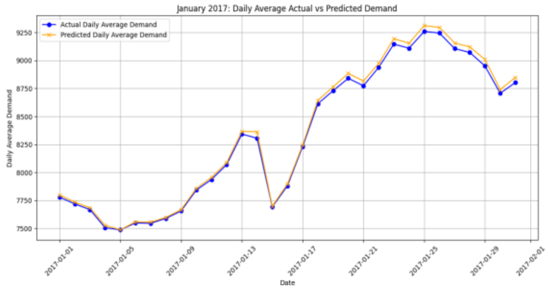

Figure 3:Daily average actual vs Predicted demand

Figure 3 showcases the performance of a Recurrent Neural Network (RNN) in predicting the daily average demand for January 2017. The actual demand is represented by the blue line, while the orange line indicates the predicted demand, allowing for a detailed day-by-day comparison. The RNN effectively tracks the actual values, capturing key trends, fluctuations, and peaks, such as the decline around January 5th and the sharp increase near January 20th. The small discrepancies between the actual and predicted values highlight the model's accuracy and its capability to generalize effectively to previously unseen data.

Metrics	Training Metrics	Testing Metrics
MAE	31.082313735293432	49.01421141266181
RMSE	43.23366698164158	49.01421141266181
R-square	0.9944984763080039	0.9911792260740875
MAPE	0.4124782870985065%	0.42125066390990945%

Figure 4: RNN training metrics & testing metrics

Date Actual	Actual Demand	Predicted Demand
2017-01-01	7780.477173	7798.533691
2017-01-02	7718.957357	7735.466309
2017-01-03	7668.654846	7684.084473
2017-01-04	7506.323283	7527.794434
2017-01-05	7487.966431	7488.203125
2017-01-06	7548.997335	7559.372559
2017-01-07	7546.253988	7556.460449
2017-01-08	7590.217977	7598.952637
2017-01-09	7655.787638	7667.031250
2017-01-10	7842.543884	7856.390625
2017-01-11	7937.222494	7955.390625
2017-01-12	8069.732869	8087.089844
2017-01-13	8342.208822	8366.719727
2017-01-14	8305.199076	8362.572266
2017-01-15	7692.589946	7698.878418

Figure 5: Actual and Predicted demand of January 2017

Date	Actual Demand	Predicted Demand
2017-01-16	7880.846456	7897.604004
2017-01-17	8231.115478	8244.317383
2017-01-18	8612.790182	8643.813477
2017-01-19	8728.835327	8763.065430
2017-01-20	8840.079509	8883.524414
2017-01-21	8773.516113	8815.461914
2017-01-22	8936.500936	8971.679688
2017-01-23	9145.475830	9193.758789
2017-01-24	9108.632609	9153.268555
2017-01-25	9258.504476	9310.000000
2017-01-26	9243.661784	9294.186523
2017-01-27	9105.436686	9155.584961
2017-01-28	9070.595744	9120.521484
2017-01-29	8949.267130	9007.463867
2017-01-30	8706.484049	8739.765625
2017-01-31	8802.548869	8847.871094

Figure 6: Actual and Predicted demand of January 2017

5.2. Convolutional Neural Network (CNN) results

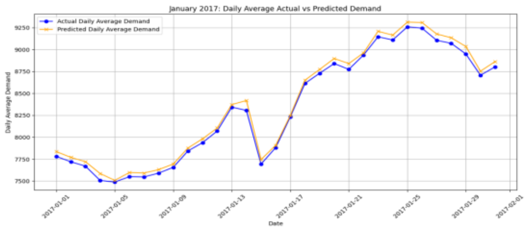

Figure 7: Daily average actual vs Predicted Demand

Figure 7 showcases the performance of the Convolutional Neural Network (CNN) model in forecasting daily average demand for January 2017. The blue line represents actual demand, while the orange line shows predicted demand, providing a day-by-day comparison. The CNN accurately captures overall trends and variations, including the dip around January 5th, the rise near January 13th, and the sharp increase around January 20th, followed by a gradual decline.

The minimal gaps between actual and predicted values highlight the model's high accuracy and ability to learn temporal dependencies. This strong alignment is further supported by performance metrics like MAE, RMSE, and R², confirming the CNN's reliability and effectiveness in demand forecasting.

Metrics	Training Metrics	Testing Metrics
MAE	58.74443774715556	59.056665074813246
RMSE	79.43315236412585	81.91291707261973
R-square	0.9796800330582526	0.9800080806050634
MAPE	0.8040128277564649%	0.7923180545975249%

Figure 8:CNN training metrics and testing metrics

Date	Actual Demand	Predicted Demand
2017-01-01	7780.477173	7835.569824
2017-01-02	7718.957357	7769.184082
2017-01-03	7668.654846	7719.770996
2017-01-04	7506.323283	7585.414062
2017-01-05	7487.966431	7506.927246
2017-01-06	7548.997335	7596.564941
2017-01-07	7546.253988	7590.662598
2017-01-08	7590.217977	7629.917969
2017-01-09	7655.787638	7693.609375
2017-01-10	7842.543884	7876.117676
2017-01-11	7937.222494	7980.974121
2017-01-12	8069.732869	8103.775391
2017-01-13	8342.208822	8371.526367
2017-01-14	8305.199076	8418.149414
2017-01-15	7692.589946	7744.876953

Figure 9:Actual and Predicted demand of January 2017

Date	Actual Demand	Predicted Demand
2017-01-16	7880.846456	7907.333496
2017-01-17	8231.115478	8246.509766
2017-01-18	8612.790182	8649.877930
2017-01-19	8728.835327	8772.572266
2017-01-20	8840.079509	8897.253906
2017-01-21	8773.516113	8839.485352
2017-01-22	8936.500936	8960.519531
2017-01-23	9145.475830	9207.517578
2017-01-24	9108.632609	9164.166992
2017-01-25	9258.504476	9312.740234
2017-01-26	9243.661784	9308.455078
2017-01-27	9105.436686	9176.978516
2017-01-28	9070.595744	9134.592773
2017-01-29	8949.267130	9034.415039
2017-01-30	8706.484049	8752.958008
2017-01-31	8802.548869	8862.867188

Figure 10: Actual and Predicted demand of January 2017

Metrics	RNN	CNN
MAE	28.94849487264767	50.44710878393799
RMSE	33.61319582419994	54.2807355543772
R-Square	0.9970150762760105	0.9922159597173794
MAPE	0.33599527832582016%	0.6038380774104523%

Figure 11:RNN metrics vs CNN metrics

Figure 11 compares RNN and CNN models using MAE, RMSE, R², and MAPE. The RNN outperforms the CNN with lower MAE (28.95 vs. 50.45), RMSE (33.61 vs. 54.28), and MAPE (0.336% vs. 0.604%), and a higher R² (0.9970 vs. 0.9922), demonstrating superior accuracy and reliability in demand forecasting.

5.3.Comparison between RNN metrics and CNN metrics

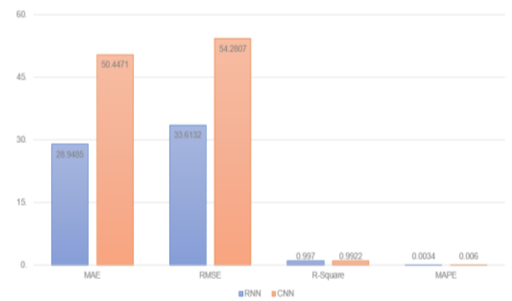

Figure 12:RNN metrics vs CNN metrics

The bar chart in Figure 12 compares RNN and CNN models across key metrics, showing the RNN outperforms the CNN in all areas. The RNN achieves lower MAE (28.95 vs. 50.45) and RMSE (33.61 vs. 54.28), higher R^2 (0.997 vs. 0.9922), and lower MAPE (0.34% vs. 0.60%), highlighting its superior accuracy and precision in demand forecasting.

6. CONCLUSION

In conclusion, the predictive analysis of energy consumption using deep learning techniques presents a significant advancement in achieving energy efficiency and sustainability. This study highlights the effectiveness of algorithms.The findings indicate that deep learning models, particularly RNNs and CNNs, outperform traditional methods in prediction accuracy and robustness, providing valuable insights for energy management. Furthermore, the integration of qualitative and quantitative metrics ensures a comprehensive evaluation of model performance, addressing critical aspects such as training time, computational cost, and interpretability.

Weather has a significant impact on energy demand, with temperature fluctuations being a major driver. During hot summer months, energy demand surges as people turn to air conditioning to cool their homes and businesses, while cold winter months see increased demand for heating. Additionally, extreme weather events such as heatwaves and polar vortexes can lead to peak energy demand, straining the grid and potentially causing power outages. Furthermore, weather conditions like cloud cover, wind, and precipitation also affect energy demand, particularly for renewable energy sources like solar and wind power. Overall, understanding the relationship between weather and energy demand is crucial for utilities and grid operators to ensure a reliable and efficient energy supply.

To sum up, the deep learning model that was created shows that it can examine the intricate relationships between a number of variables, such as the weather, the time of day, and seasonality, and how these relationships affect patterns of energy use. We can determine the most important variables influencing energy consumption, such as seasonal patterns, peak usage hours, and temperature variations, by utilizing the model's predictive capabilities. By optimizing energy supply and demand, utilities and grid operators can lower the risk of power outages and increase grid efficiency. In the end, the deep learning method for energy demand prediction analysis offers a strong instrument for well-informed decision-making, promoting a more dependable and sustainable energy future.

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