

COMPARISON BETWEEN ARIMA AND DEEP LEARNING MODELS FOR FORECASTING

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OBJECTIVE

- Project Focus: Comprehensive comparison of AutoRegressive Integrated Moving Average (ARIMA) versus deep-learning models: Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN).
- Beyond Comparison: Exploration of how each model interacts with diverse dataset characteristics, including window size, seasonality, trends, and the choice between one-step and multi-step forecasting.
- Evaluation Metrics: Utilization of essential metrics—Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Error (MAE) for rigorous Absolute performance assessment.
- Investigating how tuning hyperparameters, such as step size, prediction window, and regularization, affects the accuracy of models while forecasting

METHODOLOGY

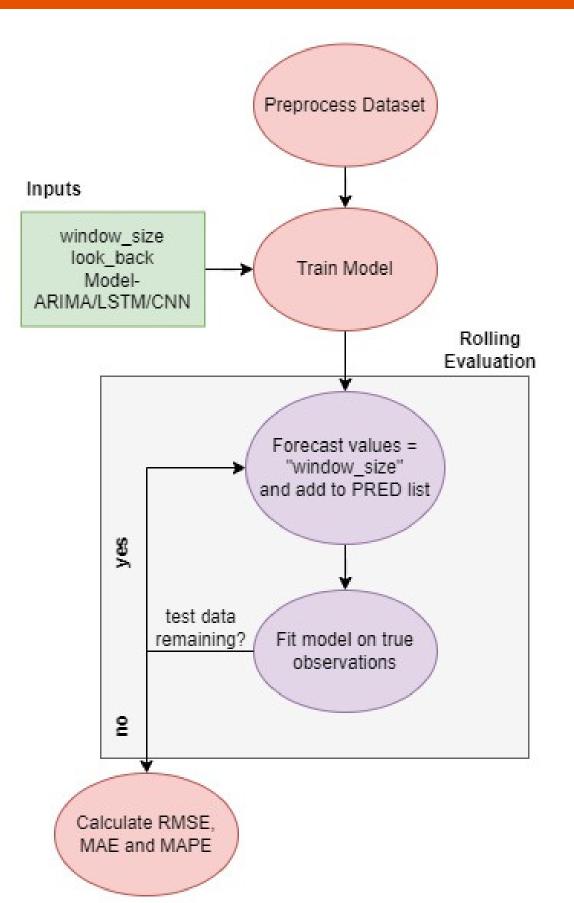


FIGURE 1: ROLLING EVALUATION

DATASET

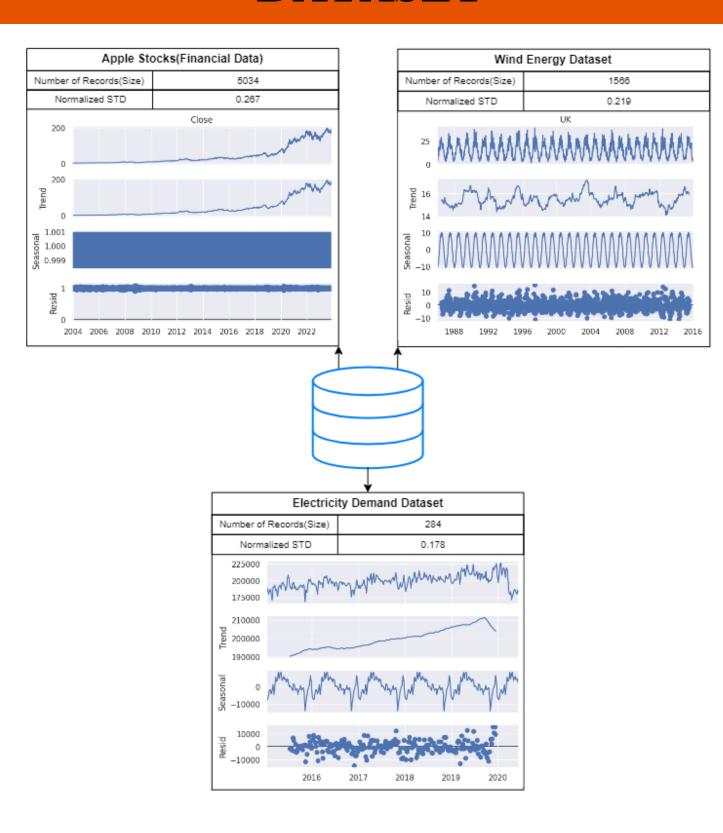


FIGURE 2: DATASET

RESULTS

1. Results on Electricity Dataset

DATASET : ELECTRICITY LOOKBACK = 1

Properties: Trend: Linear, Seasonal: True

	Tstep	sstep	istep	sstep	istep	sstep
ARIMA	8258.929 -		6534.281 -		0.032	-
LSTM	9936.293 -		8210.613 -		0.04	-
CNN	12779.624 -		9603.25 -		0.047	-
TASET : ELECTRICITY	LOOKBACK = 5					
Models	RMSE		MAI	E	MAPE	
	1step	3step	1step	3step	1step	3step
ARIMA	8164.112	9115.779	6477.497	7200.061	0.032	0.057
LSTM	9725.179	14620.289	8021.952	11504.041	0.04	0.06
CNN	13285.55	18647.398	10534.019	13679.973	0.052	0.067
TASET : ELECTRICITY	LOOKBACK = 10					
			10534.019 MAI 1step		0.052 MA 1step	
TASET : ELECTRICITY	LOOKBACK = 10	E	MAI	E	MA	PE
TASET : ELECTRICITY	LOOKBACK = 10 RMS 1step	E 3step	MAI 1step	E 3step	MA 1step	PE 3step

TABLE 1: EVALUATION ON ELECTRICITY DATASET

ARIMA consistently outperformed CNN and LSTM across horizons for the dataset with linear trend and seasonality.

2. Results on Wind Energy Dataset

DATASET: WIND LOOKBACK=1

Properties: Trend: Non Linear, Seasonal: True

Models	KIVI	OL	1417	4E	WAPE	
wodels	1step	3step	1step	3step	1step	3step
ARIMA	4.362	-	3.2	-	0.229	-
LSTM	4.712	-	3.444	-	0.245	-
CNN	4.846	-	3.52	_	0.251	-
TASET: WINI	D LOOKBACK=5					
	D LOOKBACK=5		MA	AE	MA	·PΕ
TASET: WINI			M/ 1step	AE 3step	MA 1step	NPE 3step
	RM	SE				3step
Models	RM 1step	SE 3step	1step	3step	1step	3step 0.257

Madala	RMS	RMSE		Æ	MAPE		
Models	1step	3step	1step	3step	1step	3step	
ARIMA	4.272	4.722	3.168	3.59	0.222	0.259	
LSTM	4.69	5.212	3.373	3.929	0.237	0.295	
CNN	7.286	7.643	5.301	5.762	0.373	0.416	

TABLE 2: EVALUATION ON WIND ENERGY DATASET

ARIMA consistently outperformed CNN and LSTM across various metrics (RMSE, MAPE, MSE) and prediction horizons for the dataset with nonlinear trend and seasonality.

3. Results on Financial Dataset

DATASET: FINANCIAL LOOKBACK=1

Properties: Trend: Random, Seasonal: False

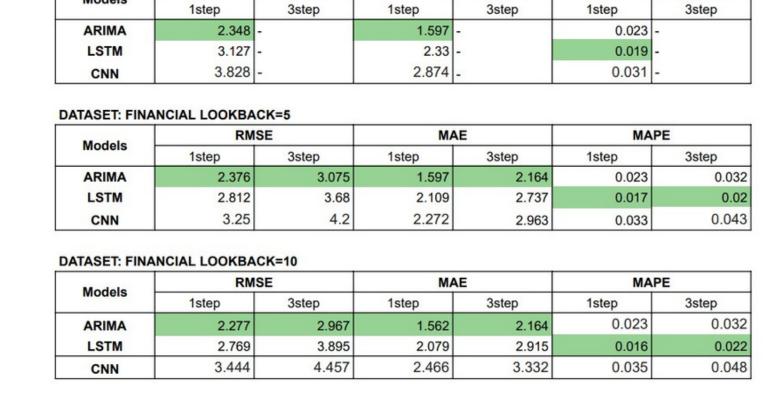


TABLE 3: EVALUATION ON FINANCIAL DATASET

ARIMA outperformed LSTM and CNN in RMSE and MAE, yet, interestingly, LSTM exhibited a better MAPE score. various metrics (RMSE, MAPE, MSE) and prediction This suggests that while LSTM produces predictions with a smaller average percentage error, occasional larger errors contribute to its higher RMSE.

Observation:

LSTM exhibits a better MAPE compared to ARIMA, but a poorer RMSE, suggesting potential overfitting. To address this, regularization is introduced for improved model stability

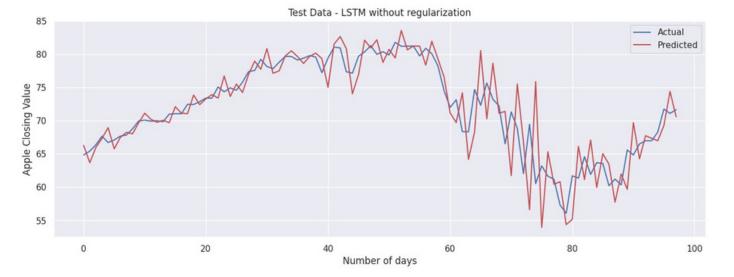




TABLE 4: REGULARIZATION IN LSTM

CONCLUSION & FUTURE SCOPE

- ARIMA excelled in diverse datasets (linear, non-linear, random), consistently outperforming LSTM and CNN.
- CNNs excel at local patterns but struggle with time series' temporal nature, leading to inferior performance.
- LSTM surprisingly surpassed ARIMA in MAPE for random indicating occasional data, significant errors.
- Regularizing LSTM enhanced forecasting accuracy, mitigating substantial errors.
- Findings highlight the importance of selecting models tailored specific data to characteristics.
- Model refinement, such as regularization, proves crucial for improving predictive capabilities.
- Assess the influence of incorporating external factors on predictive accuracy in time series forecasting.