A Performance Study of Artificial Intelligence Methods for Short-Term Energy Consumption Forecasting

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I. Overview

- Irregular human behaviors and the limitations of univariate datasets pose significant challenges to data-driven energy consumption predictions for individual households. This work presents a comprehensive performance evaluation of 35 representative AI methods for short-term energy consumption prediction in terms of accuracy, efficiency, and security. The AI methods studied include common machine learning methods (decision tree, random forest, support vector regression, multilayer perceptron), the deep learning model of Long Short-Term Memory (LSTM) and its variants (e.g., Bidirectional LSTM, Nested LSTM, Stacked LSTM), as well as hybrid methods (e.g., Convolutional Neural Network-LSTM, Empirical Mode Decomposition-LSTM, Stationary Wavelet Transform-LSTM, Empirical Wavelet Transform-LSTM, Variational Mode Decomposition-LSTM, Singular Spectrum Analysis (SSA)-LSTM, and Federated-LSTM). Empirical studies of those AI methods using the UK-DALE household datasets are conducted, revealing useful insights in choosing appropriate AI methods for short-terms prediction projects.

II. Performance Metrics

- Mean Absolute Error (MAE):

$$MAE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|,$$

- Root Mean Square Error (RMSE):

$$RMSE(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|y_i - \hat{y}_i|)^2},$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y}_i|}{y_i},$$

- Coefficient of Determination (R^2):

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(|y_i-\hat{y}_i|)^2}{\sum_{i=1}^{n}(|y_i-\bar{y}|)^2},$$

- Forecasting Trend Accuracy (FTA):

$$FTA = \frac{n_{correct}}{n},$$

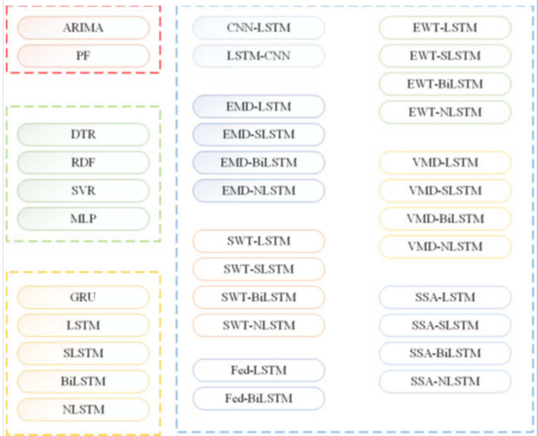
- Time (seconds)

- Security (S):

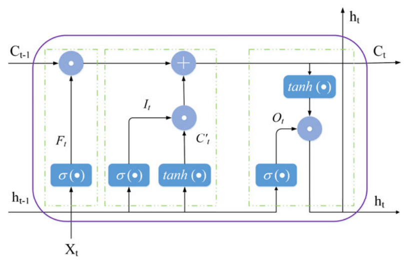
$$d(y, y_{attack}) = \frac{y_{attack} - y}{y},$$

$$S(d) = 1 - \frac{1}{1+e^{-d}}.$$

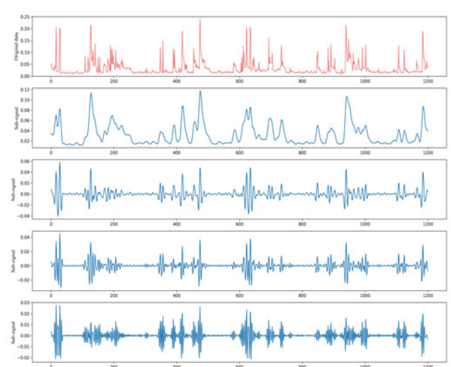
III. AI Methods Under Study



- The inner structure of LSTM neural network:



- Several subsequences of the original time series decomposed by SSA:



IV. Analysis Results

- Performance comparisons based on the average values of five households

Rank	Method	MAE	Method	RMSE	Method	MAPE (%)	Method	R²
1	SSA-SLSTM	0.0024	SSA-LSTM	0.0044	SSA-SLSTM	6.6101	SSA-LSTM	0.9886
2	Fed-BiLSTM	0.0025	SSA-SLSTM	0.0045	SSA-LSTM	7.9266	SSA-SLSTM	0.9873
3	SSA-LSTM	0.0025	Fed-BiLSTM	0.0048	Fed-BiLSTM	7.5094	Fed-BiLSTM	0.9868
4	SSA-BiLSTM	0.0031	SSA-NLSTM	0.0053	SSA-NLSTM	9.6346	SSA-NLSTM	0.9835
5	SSA-NLSTM	0.0033	SSA-BiLSTM	0.0053	SSA-BiLSTM	9.7795	SSA-BiLSTM	0.9824

Rank	Method	FTA	Method	TIME (s)*	Method	Security
1	PF	100.0000	CNN-LSTM	12.3939	EWT-NLSTM	0.4968
2	LSTM-CNN	99.9338	LSTM-CNN	14.2564	BiLSTM	0.4827
3	CNN-LSTM	99.7517	LSTM	20.4191	SVR	0.4819
4	Fed-BiLSTM	98.7933	GRU	20.5770	DTR	0.4817
5	ARIMA	95.6291	BiLSTM	39.9398	GRU	0.4791

*The training time is short, which is not taken into consideration.

PERFORMANCE OF DIFFERENT AI MODELS UNDER HOUSEHOLD1

Method	MAE	RMSE	MAPE (%)	R²	FTA	TIME(s)	Security
ARIMA	0.0249	0.0402	45.5127	-0.5838	100.0000	0.4121	0.1740
PF	0.0207	0.0398	45.2509	-0.5559	100.0000	0.0000	0.1584
DTR	0.0141	0.0307	28.6050	0.0806	51.6264	0.0755	0.5483
RDF	0.0104	0.0225	21.4986	0.5053	54.7957	2.1101	0.4662
SVR	0.0093	0.0231	16.0493	0.4802	53.6280	0.8062	0.4848
MLP	0.0107	0.0229	21.6463	0.4887	51.7932	1.8485	0.4789
GRU	0.0108	0.0226	22.4697	0.5011	52.2936	21.6162	0.4932
LSTM	0.0108	0.0226	22.6083	0.5024	51.9600	20.7444	0.4927
SLSTM	0.0111	0.0221	23.6301	0.5231	52.7940	166.2749	0.4840
BiLSTM	0.0110	0.0226	23.0772	0.5004	51.3761	100.3081	0.4950
NLSTM	0.0096	0.0218	18.4017	0.5374	53.6280	395.5088	0.4764
CNN-LSTM	0.0101	0.0226	9.8068	0.4981	99.9172	11.9970	0.4778
LSTM-CNN	0.0099	0.0223	8.9947	0.5106	99.9172	12.7379	0.4695
EMD-LSTM	0.0109	0.0174	28.2253	0.7040	54.8791	159.0231	0.4450
EMD-SLSTM	0.0097	0.0158	25.3159	0.7566	57.6314	386.1321	0.4384
EMD-BiLSTM	0.0108	0.0170	27.7761	0.7190	55.3795	150.8889	0.4459
EMD-NLSTM	0.0119	0.0171	33.1776	0.7150	57.5480	679.2749	0.4670
SWT-LSTM	0.0045	0.0092	9.3973	0.9173	69.6414	315.4587	0.3822
SWT-SLSTM	0.0051	0.0105	10.0661	0.8918	68.0567	778.5365	0.4189
SWT-BiLSTM	0.0050	0.0094	11.1059	0.9146	69.3912	417.4884	0.3940
SWT-NLSTM	0.0049	0.0093	11.3133	0.9154	70.9758	1131.8885	0.4409
EWT-LSTM	0.0112	0.0217	25.8811	0.5387	53.2944	127.7264	0.4739
EWT-SLSTM	0.0126	0.0217	31.6460	0.5403	52.6272	294.6310	0.4852
EWT-BiLSTM	0.0127	0.0224	31.6693	0.5125	55.1293	156.4443	0.4876
EWT-NLSTM	0.0249	0.0313	72.7084	0.0423	53.5446	1268.4103	0.5370
VMD-LSTM	0.0075	0.0130	16.9628	0.8338	68.8907	78.8329	0.3609
VMD-SLSTM	0.0071	0.0128	15.3669	0.8390	63.3028	211.8699	0.3364
VMD-BiLSTM	0.0081	0.0136	17.7563	0.8201	66.5555	97.9854	0.4054
VMD-NLSTM	0.0077	0.0133	17.1288	0.8276	67.1393	1405.3092	0.3855
SSA-LSTM	0.0026	0.0041	7.2230	0.9840	77.8982	102.0699	0.2432
SSA-SLSTM	0.0030	0.0048	6.9162	0.9773	77.8148	188.3849	0.2456
SSA-BiLSTM	0.0042	0.0064	9.8071	0.9605	76.2302	206.8565	0.2573
SSA-NLSTM	0.0027	0.0045	6.9679	0.9804	78.5655	582.2700	0.2448
Fed-LSTM	0.0105	0.0235	17.1366	0.4621	46.4751	788.1286	0.4830
Fed-BiLSTM	0.0022	0.0038	5.7366	0.9856	98.7587	1800.4830	0.4471

- The SSA-based models achieve high accuracy, demonstrating the effectiveness of SSA in enhancing LSTM-based forecasting.
- The hybrid models of CNN and LSTM exhibit excellent computational efficiency, indicating that CNN's feature extraction significantly accelerates LSTM's processing speed.
- EWT-NLSTM achieves the highest security score (0.4968), highlighting the strong resistance of the EWT data decomposition algorithm to interference.
- BiLSTM maintains a computation time of 39.9398s while achieving a relatively high security score of 0.4827, striking a balance between efficiency and security.

V. Summary

- Hybrid AI models generally exhibit higher accuracy than single models.
- The superior performance of SSA on different households demonstrated its strong generalization ability.
- CNN-LSTM achieves the best efficiency performance among machine learning methods.
- Federated learning, while ensuring both forecasting accuracy and privacy preservation, can effectively predict energy consumption across various households using a consistent model.
- EWT-based models exhibit the strongest anti-interference capability among data decomposition methods.

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