IOTI5 2024

In conjunction with IEEE DCOSS-IoT 2024

EXPLORING LOAD FORECASTING: BRIDGING STATISTICAL METHODS TO DEEP LEARNING TECHNIQUES IN REAL-WORLD ENVIRONMENT

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This research was funded by the European Union’s Horizon Europe Innovation Action, SINNOGENES (STORAGE INNOVATIONS FOR GREEN ENERGY SYSTEMS), under grant agreement No. 101096992. Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them.

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Motivation

- Load forecasting is **essential** for efficient **energy management** and **grid operations**.
- Accurate load forecasting enables **utility companies to make informed decisions** about generation, distribution, and maintenance
- **Traditional methods** may **not capture the complexity** of the electricity demand pattern
- **Deep Learning** offers the potential to **enhance accuracy** by capturing complex relationships
- **Emphasis** on the application of load forecasting techniques in **real-world environmental settings**, ensuring applicability to **diverse energy management scenarios**

Aim and Contribution

- **Research Aim**
  - **Prove the superiority of ML/DL in load forecasting** in terms of performance
  - Enhance **accuracy and reliability** in predicting electricity demand patterns
  - Support **efficient energy management**, **grid operations**, and **sustainable resource allocation**.
- **Contributions**
  - Deep Learning techniques can be utilized in the **context of real-world environmental settings**
  - **Complex forecasting models** can be integrated as part of a **digital twin of a real system**, as they are capable of predicting future values based on limited data, and, thus, they accurately represent actual forecasts
  - **Nonlinear patterns** that are present in current energy consumption **can be captured** by deep learning techniques

Methodology

- Comparison of:
  - ARIMA
  - SARIMAX
  - Long Short-term Memory (LSTM)
  - Deep Neural Network (DNN)

ARIMA

1. **Autoregression (AR) component**, is responsible for modeling the relationship between an observation and several lagged observations (previous time stamps). AR assumes that the value of a variable at a specific given time linearly depends on its own previous values.
2. **Differencing (I) component**, which is utilized to point out the differencing of raw observations to make the time series stationary. **Stationarity** ensures that statistical characteristics such as mean, variance, and autocorrelation remain constant through time.
3. **Moving Average (MA) component**, which models the relationship between an observation and an error from a moving average model which is applied to lagged observations, and captures short-term, and potentially random variations in the data.

SARIMAX

1. **Seasonal (S) component,** which is responsible for capturing seasonal patterns in time series data, and, simultaneously, introducing additional parameters to model seasonal variations that may exist in fixed periods.

2. **ARIMA model,** which included the autoregressive, differencing, and moving average components

3. **Exogenous Variables (X),** also known as external regressors, are factors that possibly influence the time series, and their inclusion can potentially improve the accuracy of forecasting.

Long Short-term Memory (LSTM)

1. **Memory Cell,** which enables LSTMs to keep track of captured information over long periods of time. This memory cell serves as storage and is responsible for retaining, or discarding information based on the input and internal gates.
2. **Gates,** which focus on controlling the flow of information within the network. There exist several different types of gates, such as forget, input, and output gates, each serving a different purpose.
3. **Non-linear Activation Function,** such as sigmoid, or hyperbolic tangent (tanh) to regulate the flow of information and compute the output of the aforementioned gates.

Deep Neural Network (DNN)

1. **Input Layer,** which receives the sequential data, is represented as a time series, corresponding to a feature, or a lagged value of the time data.
2. **Hidden Layers** which perform feature extraction and nonlinear transformations on the input data. It is important to note that multiple hidden layers exist, aiming to learn hierarchical representations of the time series data
3. **Output Layer,** which produces the forecasted values of the data. More precisely, in the context of time series forecasting, this layer consists of a single neuron predicting the next value in the sequence.

Dataset

- The dataset is available on HEDNO's website and includes raw and processed data (https://deddie.gr/el/themata-tou-diaxeiristi-mi-diasundedemenwn-nisiwn/leitourgia-mdn/dimosieusi-imerisiou-energeiakou-programmatismou/ησ-ικαρίας/)
- Data collected from **HEDNO's metering points** at various locations
- Live data displayed in **HEDNO's SCADA systems** and saved in **structured form in database**
- Data gathering enables DNO surveillance of **grid operation**, **real-time intervention**, **historical archive creation,** and **optimization**
- **Non-sensitive data** published for use by interested third parties
- Indicators highlight excess wind production, supporting **HEDNO's decarbonization goals**

Dataset

Feature	Description
Timestamp	**The time stamp that the measure was reported**
Mean Hourly Load	**The actual mean load of the island for the specified hourly frame in MW**
Thermal Energy Production	Thermal energy production through conventional production units in MW
Active Thermal Units	Specification of which conventional production units are actively producing at the specified time frame
Wind Energy Production	Production from wind energy of the islands Wind Parks in MW
Wind Energy Restriction Commands	Maximum allowed total production from wind energy specified by HEDNO
Maximum Potential Wind Energy Absorption	Maximum potential energy production in MW from the Wind Parks in a theoretical scenario without curtailments
Max Wind	Actual wind energy production (4.) to maximum potential energy absorption (6.) ratio
Hydroelectric Production	Total energy production that comes from Ikaria’s Hydroelectric Hybrid Station in MW

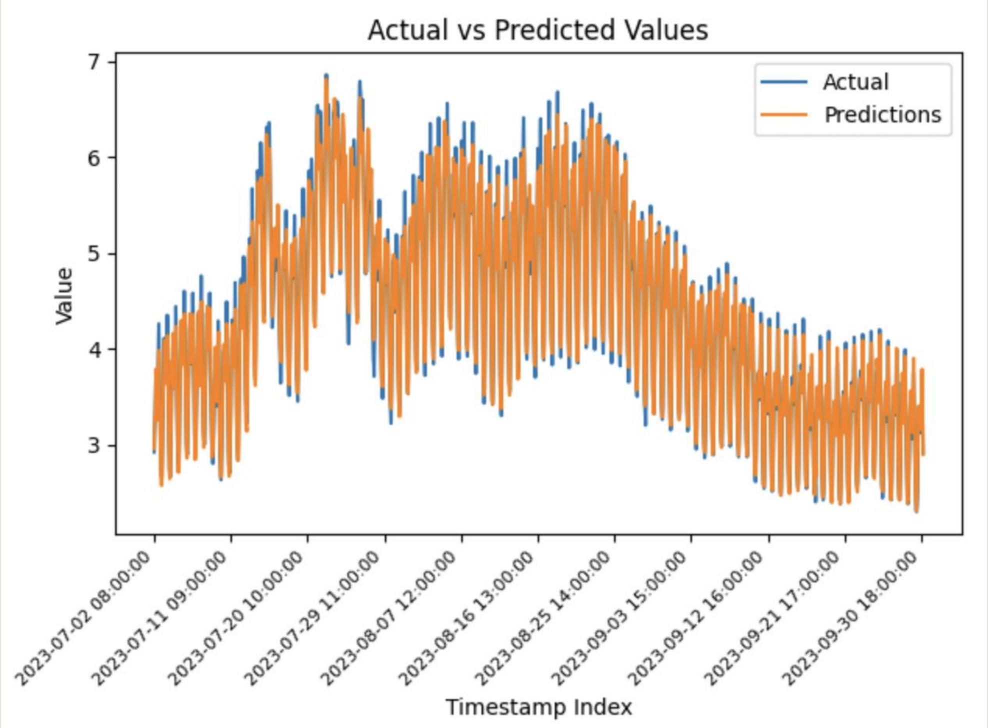
timestamp	actual_mean_hourly_load	thermal_energy_production	wind_energy_production	hybrid_production	G1	G2	G3	G4	G5	G6	G7	G8	HZ	restriction_command_to_wind_energy_park	maximum_αbsorption_of_wind_energy_production
1/2/23 0:00	3,14	1,38	0,96	0,8	1									0,97	0,97
1/2/23 1:00	2,81	1,67	0,94	0,2	1									0,95	0,95
1/2/23 2:00	2,56	1,63	0,9	0,03	1									0,91	0,9
1/2/23 3:00	2,48	1,59	0,86	0,03	1									0,87	0,87
1/2/23 4:00	2,42	1,57	0,83	0,02	1									0,85	0,85
1/2/23 5:00	2,42	1,6	0,8	0,01	1									0,85	0,85
1/2/23 6:00	2,65	1,74	0,88	0,03	1									0,93	0,93
1/2/23 7:00	3,14	2,14	0,96	0,03	1				1					0,98	0,98
1/2/23 8:00	3,31	1,73	0,87	0,71	1									0,91	0,91
1/2/23 9:00	3,51	1,81	0,89	0,82	1									0,95	0,95
1/2/23 10:00	3,58	1,65	0,86	1,07	1									0,89	0,88
1/2/23 11:00	3,51	1,46	0,9	1,16	1									0,96	0,96
1/2/23 12:00	3,47	1,44	0,87	1,16	1									0,99	0,99
1/2/23 13:00	3,5	1,53	0,82	1,15	1									0,99	0,99
1/2/23 14:00	3,61	1,55	0,92	1,14	1									0,99	0,99
1/2/23 15:00	3,81	1,69	0,97	1,16	1									0,99	0,99
1/2/23 16:00	3,92	1,66	0,94	1,32	1									0,99	0,99
1/2/23 17:00	4,2	1,66	0,89	1,65	1									0,99	0,99
1/2/23 18:00	4,59	1,82	0,85	1,92	1									0,99	0,99
1/2/23 19:00	4,58	1,62	0,77	2,19	1									0,99	0,99
1/2/23 20:00	4,57	1,7	0,69	2,18	1									0,99	0,99
1/2/23 21:00	4,31	1,55	0,67	2,08	1									0,99	0,99
1/2/23 22:00	3,99	1,77	0,58	1,64	1									0,99	0,99
1/2/23 23:00	3,5	1,78	0,52	1,21	1									0,99	0,99
2/2/23 0:00	2,99	1,97	0,1	0,92	1									0,99	0,99
2/2/23 1:00	2,65	1,92	0,12	0,61	1						1			0,95	0,95
2/2/23 2:00	2,47	1,93	0,1	0,44	1						1			0,86	0,86
2/2/23 3:00	2,39	1,92	0,02	0,44	1									0,85	0,85
2/2/23 4:00	2,34	1,89	0,01	0,44	1									0,84	0,84
2/2/23 5:00	2,34	1,83	0,07	0,44	1									0,81	0,81

Results: Evaluation Metrics

- Root Mean Square Error. $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_{pred_i})^2}$
- Mean Absolute Error. $MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - y_{pred_i}|$
- Mean Absolute Percentage Error. $MAPE = \frac{100\%}{N}\sum_{i=1}^{N}|\frac{y_i - y_{pred_i}}{y_i}|$

Results: Experimental Outcomes

	RMSE	MAE	MAPE
ARIMA	1.20	0.95	25.05%
SARIMAX	4.02	3.77	92.78%
LSTM	0.14	0.11	2.45%
DNN	**0.13**	**0.09**	**2.11%**



Conclusion and Future Work

- **Conclusion**
  - **Comparative analysis** of load forecasting techniques reveals insights into predictive modeling in energy management and proves the superiority of ML/DL Techniques
  - **Deep learning methods**, specifically LSTM and DNN, **outperform traditional statistical methods** like ARIMA and SARIMAX in real-world load forecasting
- **Future Work**
  - Deep learning model implementation requires careful consideration of **resources, complexity, data, and response time**.
  - Future research aims to improve **transparency and explainability** of deep learning methods in load forecasting.
  - **Ensemble techniques** can enhance predictive capabilities by combining various forecasting methods with external factors like weather or economics

Thank you for your attention!

Any Questions?

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