Bayesian-optimized bidirectional LSTM regression model for non-intrusive load monitoring

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ABSTRACT

In this paper, a Bayesian-optimized bidirectional Long Short-Term Memory (LSTM) method for energy disaggregation is introduced. Energy disaggregation or the so-called Non-Intrusive Load Monitoring (NILM) is a process aiming to identify the individual contribution of appliances in the aggregate electricity load. The proposed method, called Bayes-BiLSTM is organized in a modular way to address multi-dimensional issues that arise when the number of appliances increases. In addition, a non-causal model is introduced in order to tackle with inherent structure, characterizing the operation of multi-state appliances. Furthermore, a Bayesian-optimization framework is used to select the best configuration of the proposed regression model, thus improving performance. Experimental results indicate the proposed method’s superiority, compared to the current state-of-the-art.

Contribution

The proposed appliance-based, Bayesian-optimized BiLSTM regression model satisfies a set of crucial characteristics making it superior than the other NILM (Non-Intrusive Load Monitoring) methods. These specific features are summarized below:

- Long Term Regressions: This work addresses NILM as a sequence-to-sequence regression problem, thus allowing to estimate all the necessary information. Additionally, existing long-term dependencies should be accounted for, increasing regression performance.
- Modularity: Our approach is conducted for each device separately with an appliance-based modular and extendible model, thus addressing dimensionality issues.
- Optimization: Bayesian optimization strengthens model’s performance through the optimized hyperparameters selection, creating a unique optimal model, adaptable to each appliance’s individual settings and seasonal variations.
- Non-causality: In our approach, non-causality is achieved by modifying the conventional LSTM (Long Short-Term Memory) network taking into account both previous and future states of electricity power load. Therefore, bi-directional recurrent regression deep models are adopted for NILM.

Methodology

Let M be a set of all known household’s appliances. Let \( p(n) \) be the aggregate measured energy signal at time \( n \). Let \( \hat{p}(n) \) be the active power load of \( M \) appliances at time \( n \). Available \( p(n) \) can express \( \hat{p}(n) \) as [1]:

\[
\hat{p}(n) = \sum_{m=1}^{M} \alpha_m p_m(n)
\]

where \( \alpha_m \) is the noise of the measurements. So, the value \( \hat{p}(n) \) expressed as:

\[
\hat{p}(n) = \sum_{m=1}^{M} \alpha_m p_m(n) = \sum_{m=1}^{M} \alpha_m \cdot f(p_m(n))
\]

where \( f(p_m(n)) \) is the aggregate signal over a time window K and \( \alpha_m \) is a non-linear function. One way to approximate the unknown relationship \( \alpha_m \) is through a feed-forward neural network:

\[
\hat{p}(n) = \sum_{m=1}^{M} \alpha_m \cdot f(p_m(n)) = \sum_{m=1}^{M} W_m \cdot \sigma(p_m(n)) + b
\]

where \( W_m, \sigma, b \) are weights connecting the input and the hidden layers, and \( \sigma(p_m(n)) \) is a state vector gathering all hidden layer responses at time \( n \) time period. These non-linear transformations are linearly combined to provide the estimate of \( \hat{p}(n) \), using a set of weights \( W_m, \sigma, b \).

TABLE I. Performance evaluation has been performed among Bayes-BiLSTM and other approaches, such as CNNs, understanding LSTM, and FHMM. The table shows the mean absolute error (MAE) for four successive iterations. The best performing method is that of LSTM + FHMM compared to that of CNN (marked with an asterisk).

Comparisons

Next, we perform comparisons using the Estimated Energy Fraction Index (EEFI) and Actual Energy Fraction Index (AEFI) indicators defined as:

\[
\text{EEFI} = 1 - \frac{\sum_{j=1}^{M} |e_j|}{\sum_{j=1}^{M} |r_j|}
\]

\[
\text{AEFI} = 1 - \frac{\sum_{j=1}^{M} |e_j|}{\sum_{j=1}^{M} |r_j|}
\]

where \( e_j \) is the active power load of the \( j \)-th appliance and \( r_j \) is the ground truth (grey filled).

For each approach, we have built a Bayesian-optimized BiLSTM regression model using Bayes Optimization to optimally estimate the structure of each appliance’s Bayes-BiLSTM model, as illustrated in the figure showing the proposed methodology’s adopted structure (Fig. 4). The above figure also shows the CDE’s validation performance and the model’s hyperparameters respectively for four locations in residence. The final iteration performs best, as expected.

Conclusions

We propose a Bayesian-optimized Bidirectional LSTM regression model for NILM. The Bayes-BiLSTM model introduces (i) a modular approach is NILM, which addresses dimensionality issues in cases of large number of appliances; (ii) a non-causal framework taking into account the inherent structure, which characterizes the operation of multi-state appliances; (iii) a Bayesian optimization process ensuring the creation of a best fitting configuration for each appliance. Our proposed method is compared to the current state-of-the-art methods.

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References