CASCaded DEEP HYBRID MODELS FOR MULTISTEP HOUSEHOLD ENERGY CONSUMPTION FORECASTING

UNDER CONSIDERATION AT PATTERN RECOGNITION LETTERS

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ABSTRACT

Sustainability requires increased energy efficiency with minimal waste. The future power systems should thus provide high levels of flexibility in controlling energy consumption. Precise projections of future energy demand/load at the aggregate and on the individual site levels are of great importance for decision-makers and professionals in the energy industry. Forecasting energy loads has become more advantageous for energy providers and customers, allowing them to establish an efficient production strategy to satisfy demand. This paper introduces two hybrid cascaded models for forecasting multistep household power consumption in different resolutions. The first model integrates Stationary Wavelet Transform (SWT), as an efficient signal preprocessing technique, with Convolutional Neural Networks and Long Short Term Memory (LSTM) units. The second hybrid model combines SWT with a self-attention based neural network architecture named transformer. The major constraint of using time-frequency analysis methods such as SWT in multistep energy forecasting problems is that they require sequential signals, making signal reconstruction problematic in multistep forecasting applications. The cascaded models can efficiently address this problem by using recursive outputs. Experimental results show that the proposed hybrid models achieve superior prediction performance compared to existing multi-step power consumption prediction methods. The results will pave the way for more accurate and reliable forecasting of household power consumption.

Keywords  Power Consumption Forecasting, Deep transformers, Conventional Neural Networks, Long Short Term Memory, Stationary Wavelet Transform

1 Introduction

Recent rapid economic growth and development have increased the global use of electricity worldwide [Sajjad et al., 2020]. According to the International Energy Agency (IEA) World Energy Outlook 2019 report, the global energy demand rises by 2.1% per year, and the trend will continue until 2040, which is twice as much as expected in the started policies scenario [IEA, 2019]. The housing industry accounts for 27% of the world’s demand for power, which considerably impacts the overall consumption of electricity [Nejat et al., 2015]. Effective forecasting of energy consumption could potentially maintain higher stability of power supplies, especially in hybrid power generation systems [Kim and Cho, 2019]. In recent decades, many models have been developed to predict energy consumption in several building types [Li et al., 2017]. Forecasting energy consumption is essential for the accurate assessment of the economic, social, and environmental factors that cause recurrent fluctuations in energy demands. Smart grids equipped with the latest machine learning technologies will offer more flexibility in the generation and distribution of energy. For instance, smart grids can dynamically react to the energy demand changes and effectively distribute energy generated from renewable sources [Siano, 2014]. Power usage prediction has recently been the focus of researchers and manufacturers as this is a key and important task for economically effective operation and controls [Dong and Yang, 2020]. Accurate load forecasting ensures safe and reliable power systems operation [Roldán-Blay et al., 2013]. With the complexity of the power systems, predicting the energy consumption of modern buildings is deemed challenging.
The prediction of household energy usage is often affected by several elements, such as the type of electrical equipment and appliances inside the house, their geographical locations, and their activity time [Ahmad et al., 2014].

Based on the time horizon, electrical load forecasting models may be classified into four prime categories: very short-term, short-term, medium-term, and long-term prediction [Eskandari et al., 2021]. Numerous load forecasting methods have been presented to address such forecasting problems. These methods are categorized into three main types: (i) engineering approaches, which compute thermal dynamics and energy behavior for the entire buildings, (ii) statistical techniques, which explore the relationship between energy consumption and other elements such as climatic data and occupation, and (iii) machine learning techniques, which focus more on learning the distinguishable energy usage patterns from the historical data. However, both engineering and statistical methods were found to be unreliable and less generalizable in real-life conditions, especially when tested on unseen data at a new site [xiang Zhao and Magoulès, 2012, Kaboli et al., 2016].

Statistical techniques were used mainly for predicting energy demands. For instance, the autoregressive integrated moving average (ARIMA) model was applied to forecast power consumption [Kandananond, 2011]. Hadri et al. [2021] have evaluated three different models, seasonal ARIMA (SARIMA), XGBOOST, and LSTM, for forecasting power consumption. Their results showed that the XGBOOST model is able to achieve higher prediction performance in the one-minute ahead forecasting problem compared to other methods. In an attempt to solve the volatility problem in energy consumption data, singular spectrum analysis (SSA) and parallel LSTM (pLSTM) neural networks were integrated to better forecast power consumption [Jin et al., 2022].

In the past few years, several machine learning-based energy consumption prediction models have been proposed. For instance, a model based on LSTM and a sine cosine optimization algorithm was proposed by [Somu et al., 2020], which improved the short-term forecasting accuracy by around 12% and long-term forecasting by 60%. A dilated convolutional neural network (DCNN) was also combined with bidirectional LSTM (BiLSTM) to efficiently control power usage in integrated local energy systems between consumers and suppliers [Khan et al., 2021]. Hu et al. [2020] combined echo state network, bagging, and a differential evolution algorithm to improve energy consumption forecasting accuracy. A combination of progress learning and deep learning was introduced to address nonlinear and complex energy consumption forecasting. Their proposed model improved the root mean squared error (RMSE) by more than 17% compared to traditional backpropagation neural networks [Liu et al., 2020]. An ensemble hybrid model was also proposed to predict the cyclic and stochastic components of building energy in [Zhang et al., 2020]. Obtained results showed that the cyclic features can improve the prediction RMSE by 30%. A hybrid forecasting model based on data mining techniques and the Box-Jenkins method was presented to capture the nonlinear and complex patterns in peak load and energy demand data [Kazemzadeh et al., 2020]. A hybrid model based on empirical mode decomposition and extreme gradient boosting was proposed to deal with the high nonlinearity of energy consumption prediction [Li et al., 2020]. Convolutional networks were integrated with Gated Recurrent Units (GRU) in [Sajjad et al., 2020], and with LSTM [Kim and Cho, 2019] to better leverage the spatio-temporal features and improve the overall prediction performance. Experiments showed that hybrid CNN-GRU networks are 50% more accurate than hybrid CNN-LSTM. To reduce volatility and expand data dimensionality, the stationary wavelet transform (SWT) was combined with LSTM units to forecast energy consumption [Yan et al., 2019]. Results revealed that using SWT for data pre-processing...
can remarkably improve LSTM forecasting performance. Transformer networks were recently proposed to overcome LSTM’s parallelization problem [Vaswani et al., 2017]. Transformer-based models can efficiently capture complex time-series data dynamics that are difficult to extract with traditional sequence models like recurrent neural networks (RNNs) [Wu et al., 2020].

Energy usage patterns in individual households are typically irregular due to a variety of factors, such as weather and holidays. As a result, methods that anticipate energy usage solely using energy consumption statistics are not accurate enough. Therefore, including other observations (whether the observed point is an anomaly, a change point, or a pattern) may help boost the prediction performance [Li et al., 2019]. The similarities between distinct data encoding variables in transformers (e.g., queries and keys) are determined based on their point-specific values rather than taking local contexts into account [Lin et al., 2020]. This problem might be solved by either introducing an efficient attention mechanism to replace the traditional self-attention module (SAM) of transformers, such as the Spring Time Warping Matrix [Lin et al., 2020], or externally providing additional information about the surroundings of the observed point to the transformer [Yan et al., 2019]. The proposed forecasting strategy in this paper is based on the latter approach. The SWT is effective when combined with other machine learning models, and it has been proven to be an efficient pre-processing approach that decomposes a given time-series signal into high- and low-frequency sub-signals, revealing distinct patterns from the actual observations [Yan et al., 2019]. In a previous paper [Saad Saoud et al., 2022], a hybrid model based on the transformers and SWT was proposed to forecast one step ahead energy consumption. It has been shown that integrating SWT with transformer networks is 48% more accurate than the SWT’s hybridization with LSTM. A fundamental drawback of using SWTs in multistep forecasting is that they require sequential signals for reconstruction, but sequences of future samples don’t exist when solving multistep prediction problems.

Despite great efforts to improve household energy consumption forecasting, previous methods still have some limitations that need to be addressed. (i) In multistep forecasting problems that are based on decomposition/reconstruction, it is not possible to reconstruct the forecasted signal from its wavelet coefficients due to the unavailability of future data, i.e., SWT coefficients need to be forecasted first in order to reconstruct the signal. (ii) Deep learning models require a large amount of training data and high computational power.

To fill the aforementioned research gap, we propose hybrid cascaded deep learning-based models that combine either the CNN-LSTM or Transformer with the SWT to accurately predict household energy consumption. This is an extension of previous studies that showed great potential for integrating SWT with deep learning [Yan et al., 2019, Saad Saoud et al., 2022]. The proposed models extend the usage of the SWT-based hybrid predictors to multistep forecasting problems, in which future data are needed for signal reconstruction.

The main contributions of this work can be summarized as follows:

- We developed two hybrid SWT-Deep learning models to forecast multistep residential energy consumption. The deep learning models predict the SWT’s energy consumption-related features and feed them recursively along the forecasting horizon to predict the next steps. This combination helps in describing the irregular patterns in univariate household energy data and resolves the multistep SWT reconstruction issue. This is the first time, to the best of our knowledge, that a combination of SWT and deep learning models is used to create a multistep energy consumption prediction model.
- Experiments based on a benchmark energy consumption dataset and for different time resolutions reveal that the proposed SWT-deep learning models can effectively forecast home energy usage and outperform concurrent and previous prediction methods.

2 The Proposed Model

We propose two hybrid prediction methods based on the stationary wavelet transform and two deep neural network architectures (CNN-LSTM and Transformer) for forecasting household energy consumption. First, the univariate energy input data is decomposed into approximation and detail subbands using SWT to extract the distinguishable patterns needed for accurate predictions. Second, the wavelet sub-bands are supplied to either a CNN-LSTM network or a deep transformer network in order to forecast the next wavelet sub-bands. Finally, the inverse SWT is applied to the outputs of deep learning models to reconstruct the predicted household energy consumption. A schematic diagram of the proposed prediction methods is shown in Figure 1.

2.1 The stationary wavelet transform

The wavelet transform divides the energy consumption signal into levels; the resultant subsignals are half the length of the approximation signal at the previous wavelet level. The stationary wavelet transform (SWT) [Nason and Silverman]...
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Figure 2: (a) Time2Vec block, (b) the proposed deep transformer-based SWT forecasting model, and (c) the encoder block

Figure 3: N-level SWT decomposition

was introduced to address shift-invariance and non-redundancy limitations of discrete wavelet transform (DWT) [Supratid et al., 2017, Ilker Güven and Simsir, 2020]. Instead of down-sampling the data after applying the low-pass or high-pass filters in the DWT, SWT adjusts the filters at each decomposition level by padding zeroes [Hadiyan et al., 2020]. The SWT eliminates the down-sampling operator from the standard DWT implementation. The generated sub-signals in the SWT have the same length as the source signal, which is a desirable attribute for the proposed forecasting model. Using the SWT offers three advantages: 1) Unlike conventional wavelets, the SWT sub-signals have the same length as the original signal, which makes it most suitable for neural networks, 2) the SWT sub-bands include crucial information needed for accurate prediction and, 3) the SWT has a low computational cost, which makes it a perfect candidate for real-time analyses and predictions [Zhou et al., 2020]. Therefore, we use the SWT to produce identifiable low- and high-frequency components (known as approximations and details) that well represent the energy consumption time-series data. These components are then used as inputs to either the CNN-LSTM architecture or the deep transformer for energy consumption prediction. The SWT approximation sub-band depicts the time-series overall trend, and the detail sub-band shows small series deviations. The SWT deconstructs the time series using a hierarchical mix of low-pass and high-pass wavelet filters, allowing high and low frequencies to be separated. The breakdown can be shown as a dyadic tree form [Talaat et al., 2020] (see Figure 3). We examined four wavelet families and five decomposition levels, and our results reveal that the Daubechies (db1) with three levels produce minimum prediction errors. It should be noted that the inverse SWT (ISWT) only needs the details and the last approximation signals to reconstruct the original signal, but we have noticed that using all sub-signals improves the results. Therefore, we have used all six wavelet features to train the networks. The total number of wavelet features used is $6 \times N$, where $N$ is the total number of samples.
2.2 SWT-deep learning model

The proposed hybrid deep learning-based energy consumption methods integrate SWT with either CNN-LSTM or Transformer network.

First, we decomposed the energy consumption dataset into sublevels using SWT. Then, we applied the deep learning models to forecast the next SWT coefficients \( \hat{y}(t + 1) \) using the \( n \) past values of the SWT coefficients \([y(t-n), y(t-n+1), \ldots, y(t)]\). The ISWT was applied to the predicted coefficients to have the one step ahead predicted energy value \( \hat{P}(t + 1) \). The predicted SWT coefficients \( \hat{y}(t + 1) \) were also supplied together with the shifted SWT coefficients vector to the deep learning models to forecast the next SWT coefficients \( \hat{y}(t + 2) \). This procedure is recursively applied until the prediction of all values of the entire horizon is achieved. Note that we trained the network to forecast one step ahead, and then it was fine-tuned sequentially for the next steps.

We examine the performance of both CNN-LSTM and Transformer networks for automated feature learning and prediction. LSTM is a type of recurrent neural network that may learn long-term relationships, particularly in sequence prediction issues. A cell, an input gate, an output gate, and a forget gate comprise a typical LSTM unit. The following are the equations describing a forward pass of the LSTM cell [Abadi et al., 2016; Hochreiter and Schmidhuber, 1997]:

\[
\begin{align*}
    i_t &= \sigma_1(W_i x_t + U_i h_{t-1} + b_i) \\
    f_t &= \sigma_1(W_f x_t + U_f h_{t-1} + b_f) \\
    o_t &= \sigma_1(W_o x_t + U_o h_{t-1} + b_o) \\
    c_t &= \sigma_2(W_c x_t + U_c h_{t-1} + b_c) \\
    h_t &= o_t \odot c_t
\end{align*}
\]

where \( x_t \) and \( h_t \) are the cell’s hidden input and output at time step \( t \), respectively. The matrices \( W_q \) and \( U_q \) hold the weights of the input and recurrent connections, respectively. \( b_q, q = \{ i, f, o, c \} \) is the bias. The hidden output \( h_t \) is computed using equations (1) to (6), where \( i \) is the input gate, \( o \) is the output gate, \( f \) is the forget gate, and \( c \) is the memory cell. \( \sigma_1 \) and \( \sigma_2 \) are the sigmoid and hyperbolic tangent activation functions, respectively. The initial values are \( c_0 = 0 \) and \( h_0 = 0 \) and the operator \( \odot \) denotes the Hadamard product.

The proposed CNN-LSTM-SWT network uses three 1D convolutional layers with Rectified Linear Unit (ReLU) activation function. The CNN layers are followed by two layers of LSTM cells and two fully connected layers. The fully connected layer uses ReLU and linear activation functions. We also used dropouts in the LSTM and fully connected layers to address model overfitting.

Figure 2 depicts the schematic diagram of the transformer-based SWT decomposition and reconstruction model for multistep time series prediction. The model contains one Time2Vec block followed by three encoder blocks and one global average pooling, then two sequential dropout-dense layers. The transformer is a deep learning architecture that relies heavily on attention mechanisms to analyze sequential input data. Unlike previous sequence models, the transformer relaxes the need for using convolutional or recurrent neural networks, it employs stacked multi-head self-attention units and fully connected layers. Each layer begins with a multi-head self-attention layer, followed by two feedforward levels. Both multi-head attention and feedforward layers are followed by dropout and Add&Normllize layers. The proposed prediction method takes advantage of the transformer’s encoder structure only while ditching the decoders completely. The SWT coefficients are passed through the Time2Vec block before going to the encoders (Figure 2). The Time2Vec [Kazemi et al., 2019; Shen et al., 2020] is an expanded and learnable version of the transformer’s initial positional encoding layer. It permits learning the input frequencies rather than utilizing a fixed representation (see Figure 1(a)). The Time2Vec operation implements the following equation [Kazemi et al., 2019]:

\[
    Time2Vec(\tau)[i] = \begin{cases} 
    \omega_i \tau + \varphi_i, & \text{if } i = 0 \\
    \sin (\omega_i \tau + \varphi_i), & \text{if } 1 \leq i \leq k
    \end{cases}
\]

where, \( Time2Vec(\tau)[i] \) is the \( i^{th} \) element of \( Time2Vec(\tau) \) that has \( k \) elements, and \( \omega_i \) and \( \varphi_i \) are learnable parameters.
The encoder comprises a set of sub-encoders that handle each layer’s input sequentially. Each encoder layer generates encodings of essential information based on the portions of the inputs that are significant to one another (Figure 2(c)). Next, the encodings are passed into the next encoder layer, which uses attention mechanisms to compute the relevance of each input. Encoder layers include residual connections, layer normalization operations, and feedforward networks for further output processing. Each multi-head attention system has three learnable weights: query weights $Q$, key weights $K$, and value weights $V$ [Liu et al., 2020]. More specifically, the transformer’s multi-head attention module conducts its computations in parallel (Figure 4). The attention module conducts an attention mechanism repeatedly in parallel. A single attention module output is given by [Liu et al., 2020]:

$$\text{Att}_j = \text{softmax}(\frac{QK}{\sqrt{d_k}})V$$ \hspace{1cm} (8)

where: $j = 1, \cdots, h$, and $d_k$ is the dimension of query and key vectors. The multi-head attention score is the concatenation of the output of $h$ heads given by Eq. 9 multiplied with learnable projection parameters $W$, i.e.:

$$\text{MultiheadAtt.} = \text{Concat}(\text{Att}_1, \cdots, \text{Att}_h)W$$ \hspace{1cm} (9)

With multi-head attention, the transformer may encode multiple relationships and nuances for each input variable. The parameters used to set up our networks are given as follows: batch size = 32, and the default Keras kernel initializer, i.e., Glorot uniform, was used to initialize the weights. Twelve parallel attention layers, with $Q = K = V = 256$, are adopted in the proposed method. The total number of trainable parameters of the two proposed models are 340,294 parameters for the Transformer-SWT model and 422,358 parameters for the CNN-LSTM-SWT model.

### 3 Results and discussions

**Data description:** The University of California Irvine (UCI) machine learning repository provides a power consumption dataset with 2,075,259 measurements sampled at one minute and collected between December 2006 and November 2010 at the house of Sceaux (Paris, France) [Hebrail, 2012]. Our forecasting paper focuses on global active power (i.e., we use global active power time series in the forecasting process). It should be noted that this dataset was used by many researchers to validate their models’ performance (e.g., [Mocanu et al., 2016, Marino et al., 2016]). For a fair comparison with other existing studies, we have used the same strategy applied in ([Mocanu et al., 2016, Marino et al., 2016]) to test the performance of our proposed systems. The first three years of the dataset were utilized to train the models, and the remaining dataset was used to test the models. The root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) are chosen as metrics for the models’ evaluation.

This paper proposes novel deep learning solutions to forecast multistep energy consumption for several time scales. The performance of the developed model was compared with the following models: Auto-Regressive Integrated Moving
Table 1: Comparison results of the proposed model with other existing machine learning models

| Method                      | Resolution | RMSE (kW) | MAE (kW) | MAPE (%) |
|-----------------------------|------------|-----------|----------|----------|
| ARIMA                       | Minutely   | 1.1542    | 0.6078   | 22.39    |
|                             | Hourly     | 1.0047    | 0.8376   | 155.0    |
|                             | Daily      | 0.3855    | 0.3067   | 40.37    |
|                             | Weekly     | 0.5498    | 0.4658   | 57.70    |
| SVR                         | Minutely   | 0.7120    | 0.4551   | 69.73    |
|                             | Hourly     | 0.6942    | 0.4927   | 61.87    |
|                             | Daily      | 0.3571    | 0.2709   | 29.41    |
|                             | Weekly     | 0.1790    | 0.1548   | 16.17    |
| Random Forest               | Minutely   | 0.8242    | 0.4909   | 61.87    |
|                             | Hourly     | 0.8224    | 0.6732   | 113.7    |
|                             | Daily      | 0.3484    | 0.2825   | 38.19    |
|                             | Weekly     | 0.2062    | 0.1494   | 19.72    |
| MIMO-RVNN                   | Minutely   | 0.4879    | 0.3289   | 56.25    |
|                             | Hourly     | 0.9824    | 0.7229   | 105.1    |
|                             | Daily      | 0.5380    | 0.4316   | 57.92    |
|                             | Weekly     | 0.2466    | 0.1644   | 16.25    |
| LSTM                        | Minutely   | 0.6150    | 0.3431   | 82.03    |
|                             | Hourly     | 0.6918    | 0.9268   | 107.4    |
|                             | Daily      | 0.3090    | 0.2306   | 26.26    |
|                             | Weekly     | 0.2965    | 0.1622   | 18.71    |
| CNN-LSTM [Kim and Cho 2019] | Minutely   | 0.6114    | 0.3493   | 34.84    |
|                             | Hourly     | 0.5957    | 0.3317   | 32.83    |
|                             | Daily      | 0.3221    | 0.2569   | 31.83    |
|                             | Weekly     | 0.3085    | 0.2382   | 31.84    |
| Wavelet network             | Minutely   | 0.7479    | 0.5282   | 90.37    |
|                             | Hourly     | 0.7460    | 0.5563   | 86.81    |
|                             | Daily      | 0.7893    | 0.6183   | 83.00    |
|                             | Weekly     | 0.4697    | 0.5251   | 34.18    |
| RBF network                 | Minutely   | 0.7770    | 0.5301   | 85.85    |
|                             | Hourly     | 0.7519    | 0.5624   | 88.39    |
|                             | Daily      | 0.7565    | 0.6034   | 81.03    |
|                             | Weekly     | 0.2268    | 0.1673   | 16.93    |
| Multistep CNN-LSTM-SWT (Proposed) | Minutely   | 0.4645    | 0.2060   | 33.99    |
|                             | Hourly     | 0.5102    | 0.3369   | 46.29    |
|                             | Daily      | 0.2793    | 0.2196   | 31.73    |
|                             | Weekly     | 0.1758    | 0.1261   | 12.43    |
| Multistep Transformer-SWT (Proposed) | Minutely   | 0.3929    | 0.1911   | 15.01    |
|                             | Hourly     | 0.4183    | 0.2637   | 35.04    |
|                             | Daily      | 0.2378    | 0.1832   | 21.90    |
|                             | Weekly     | 0.1574    | 0.1106   | 11.72    |

Average (ARIMA), Support Vector Regression (SVR), random forest, a multi-input multi-output real-valued neural network (MIMO-RVNN), a wavelet network, a Radial basis function (RBF) network, a Long Short Term Memory (LSTM) model, and a hybrid convolutional neural network-LSTM model (CNN-LSTM). In addition, results were compared with recently published studies addressing the same problem [Sajjad et al., 2020, Kim and Cho, 2019, Mocanu et al., 2016, Ullah et al., 2020, Marino et al., 2016]. The model settings used in our experiments are given as follows:

1) ARIMA model: the grid search algorithm [Brownlee, 2017] was used to find the optimal parameters \((p, d, q) = (0, 1, 1)\).

2) SVR model: We used the common Gaussian kernel as a kernel for the SVR model [Ahmed et al., 2010].

3) The random forest model: We used the same setting in [Shin and Woo, 2022].

4) The LSTM model: We used the same setting in [Nazir et al., 2021].

5) The MIMO-RVNN, wavelet network, and RBF network: These networks have one hidden layer. The optimal number of neurons in the hidden layer was found empirically and is equal to 100, 10, and 10 neurons for the MIMO-RVNN, wavelet network, and RBF network respectively.
Table 2: Comparison results in terms of RMSE (kW) of the proposed Multi-SWT-Deep Learning models with other existing models in the literature

| Model                              | Minutely | Hourly | Daily | Weekly |
|------------------------------------|----------|--------|-------|--------|
| CRBMs [Mocanu et al., 2016]       | 0.9032   | 0.6906 | -     | 0.1822 |
| LSTM-Seq2Seq [Ullah et al., 2020] | 0.6670   | 0.6250 | -     | -      |
| FCRBM [Mocanu et al., 2016]       | 0.6663   | 0.6630 | -     | 0.1702 |
| CNN-LSTM [Kim and Cho, 2019]      | 0.6114   | 0.5957 | 0.3221| 0.3085 |
| CNN-BDLSTM [Marino et al., 2016]  | 0.5650   | -      | -     | -      |
| CNN-GRU [Sajjad et al., 2020]     | 0.4700   | -      | -     | -      |
| CNN-LSTM-SWT (proposed)           | 0.4645   | 0.5102 | 0.2793| 0.1758 |
| Transformer-SWT (proposed)        | 0.3929   | 0.4183 | 0.2378| 0.1574 |

Figure 5: Learning curves of cascaded CNN-LSTM-SWT, cascaded transformer-SWT, MIMO-RVNN, wavelet network, and RBF network for 100 epochs

The proposed model architectures have been implemented in Keras\(^1\) with Tensorflow backend [Abadi et al., 2016] and the RMSProp learning algorithm, with a learning rate $\eta = 0.001$. As a preprocessing step, the SWT approximation and detail coefficients were normalized between 0 and 1 to speed up the learning and convergence of the proposed model.

Table 2 shows the obtained results, along with other recently published models, LSTM and CNN-LSTM [Kim and Cho, 2019]. The learning curves of the cascaded CNN-LSTM-SWT, cascaded transformer-SWT, MIMO-RVNN, wavelet network, and RBF network for 100 epochs are compared in Figure 5. It can be observed that the proposed hybrid models achieve higher performance than previous methods. Figure 6 shows a selected timestamp from the validation set of the actual and forecasted 60-minutes of energy consumption using our deep learning-SWT hybrid models. The proposed models forecast energy consumption efficiently, by predicting the global and local features of energy consumption.

Figure 6(a) demonstrates that the proposed approach can efficiently extract the irregular energy consumption patterns in the case of one-minute forecasting. Results for the hourly, daily and weekly cases are shown in Figure 6(b), Figure 6(c) and Figure 6(d), respectively. The results show that both models achieve superior performance to other models in household energy consumption. Table 2 shows the performance evaluation of the proposed technique in comparison with other recently proposed competitive methods.

The experiment was set up with the same temporal resolution of minutely, hourly, daily, and weekly units. Sajjad et al. [2020] combined CNN with GRU to forecast time series energy consumption. Kim and Cho [2019] proposed a hybrid model based on CNN and LSTM for the multivariate prediction of household energy consumption. Mocanu et al. [2016] proposed two stochastic models for time-series prediction of energy consumption, CRBM, and FCRBM. Marino et al. [2016] investigated a novel energy load prediction approach based on deep neural networks and an LSTM-based Sequence-to-Sequence (Seq2Seq). The results demonstrate that our transformer-based approach outperformed baseline power consumption prediction methods by a significant margin.

\(^1\)Chollet, F. et al. (2015). Keras. https://keras.io
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Figure 6: Performance comparison of the energy consumption prediction results for a) 60 minutes forecasting, b) 60 hours forecasting, c) 60 days forecasting, and d) 48 weeks forecasting.

Table 3: Evaluation of the most important feature in the daily case.

| Method      | Wavelet coefficients used | RMSE (kW) | MAE (kW) | MAPE (%) |
|-------------|---------------------------|-----------|----------|----------|
| CNN-LSTM-SWT| All                       | 0.2793    | 0.2196   | 31.73    |
|             | $A_3$                     | 0.2874    | 0.2270   | 32.14    |
|             | $D_3$                     | 0.9459    | 0.9015   | 100.13   |
|             | $D_2$                     | 0.9457    | 0.9015   | 100.13   |
|             | $D_1$                     | 0.9458    | 0.9015   | 100.14   |
| Transformer-SWT | All                   | 0.2378    | 0.1832   | 21.90    |
|             | $A_3$                     | 0.2501    | 0.1903   | 22.07    |
|             | $D_3$                     | 0.9878    | 0.9473   | 99.69    |
|             | $D_2$                     | 0.9899    | 0.9489   | 99.77    |
|             | $D_1$                     | 0.9917    | 0.9501   | 99.87    |

Next, we tested the performance of the proposed model across different prediction horizons. Figure 7 shows the MAE evolution across the whole testing data in the daily case. Taking the MAE of the next step forecasting as a reference, the model is 57% less accurate at sample 60, 72% less accurate at sample 120, 130% less accurate at sample 180, 220% less accurate at sample 240, and 287% less at sample 285, the last sample in our testing dataset. It should be noted that the average and the standard deviation of daily power consumption are $\mu = 1.09\text{kW}$ and $\sigma = 0.41\text{kW}$.

Finally, we tested the significance of the different wavelet features. We generated daily predictions using individual wavelet features by setting the other wavelet coefficients to zero. Table 3 shows the obtained results. One can see that the most important feature is the third approximation subband $A_3$.

Despite the efficiency of the presented models, some limitations can be addressed in future works. First, the model was trained on a specific location, making transfer learning only effective if applied to data with similar characteristics. We recommend training the model on additional data acquired at different sites and with different acquisition parameters.
to overcome this limitation. Second, the proposed models were trained and tested on noise-free and pre-processed data. Training and testing the proposed power consumption prediction methods on noisy and contaminated data can be considered in future work.

4 Conclusions

In this study, we proposed and tested two hybrid methods based on the stationary wavelet transform (SWT) and deep learning for robust predictions of residential energy consumption. SWT is used to decompose electrical energy consumption time-series data and produce distinguishable feature representations needed for accurate predictions. Deep learning models such as convolutional-recurrent neural networks and deep transformers are used to process the SWT sub-band signals and characterize household energy consumption. Such accurate energy consumption forecasting methods pave the way for more reliable power supply, effective operation, and better sustainability of electricity generation systems.

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