Energy Consumption Prediction for Multi-functional Buildings Using Convolutional Bidirectional Recurrent Neural Networks

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Abstract. In this paper, a Conv-BiLSTM hybrid architecture is proposed to improve building energy consumption reconstruction of a new multi-functional building type. Experiments indicate that using the proposed hybrid architecture results in improved prediction accuracy for two case multi-functional buildings in ultra-short-term to short term energy use modelling, with R^2 score ranging between 0.81 to 0.94. The proposed model architecture comprising the CNN, dropout, bidirectional and dense layer modules superseded the performance of the commonly used baseline deep learning models tested in the investigation, demonstrating the effectiveness of the proposed architectural structure. The proposed model is satisfactorily applicable to modelling multi-functional building energy consumption.

Keywords: Deep Learning · Energy Use Prediction · Leisure Centre

1 Introduction

As the world awakens to the need to protect and conserve the natural environment, building energy efficiency continues to take centre stage in global sustainability issues. The commonly used techniques for building energy consumption prediction (ECP) are classified under engineering methods, statistical methods and artificial intelligence-based methods [2]. Statistical methods for building ECP insist on assumptions such as stationarity of historical data, while engineering methods tend to be time-consuming as they try to account for every building parameter. Machine learning methods may fail to identify intricate building energy patterns buried in the ultra-short-term timeseries data. Deep learning methods have been adopted for building ECP with successful results, mainly because of their automatic feature extraction and higher information abstraction capabilities.

Research on building energy consumption prediction (ECP) has been underway for decades. Building ECP has been extensively researched for many building types such as office buildings, schools, hotels, commercial and residential buildings, as highlighted in the review paper [21]. However, multi-functional building types have been marginally represented in building energy literature. Data-driven techniques have been marginally applied in sports and recreation

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DOI: 10.1007/978-3-030-77977-1_23

facilities' energy consumption prediction studies. A toolkit was proposed for preliminary estimation of power and energy requirements in sports centres [5]. Artificial neural networks were designed using simulated data to predict and optimise the energy consumption of an indoor swimming pool [23].

1.1 Deep learning models review

The deep learning group of techniques provide a practical approach to building energy consumption prediction. The monthly energy consumption of customers of an energy company was forecasted in [6] using three deep learning models. The fully connected MLP, Long Short-Term Memory neural networks and convolutional neural networks were tested on their prediction skill based on the MAE, RMSE, MSE and (R^2) metrics. The LSTM model was reported as the superior model, while both the MLP and CNN did not show significant differences. Deep recurrent networks and MLP were studied for residential and commercial buildings for medium to long term predictions [17]. The findings highlighted the better performances of the recurrent networks. Deep highway networks and ensemble-based tree methods were used in short-term building energy prediction, with the former reported being superior to its counterpart models in [1]. Day-ahead multi-step forecasting of commercial buildings energy consumption was studied in [9] using CNN, recurrent neural network and seasonal ARIMA models. In this work, the temperature-based CNN model was reported as the superior model using one-year-long historical data, while the SARIMA model was noted as the inferior model. At the district level, [3] demonstrated the superior performance of the deep learning models for short-term load forecasting in commercial buildings; however, a deterioration in performance as forecasting horizon increases was noted. An effective genetic algorithm-LSTM hybrid was developed in [4] for buildings ECP. Aggregated power load and photo-voltaic power output were successfully predicted using a recurrent neural network and an LSTM hybrid model [22]. The aggregate residential building active power use estimation was tested using conditional restricted Boltzmann machines (FCRMB) and factored restricted Boltzmann machine, artificial neural network, recurrent neural network and support vector machines by [16] for different prediction horizons, and the authors reported the superiority of FCRMB over other tested models. The IHEPC dataset on the UCI Machine Learning Repository spans, which over almost four years, was used to develop a CNN-LSTM model which outperformed the prior FCRMB model in [13]. In another work, a CNN and multilayer bidirectional LSTM model was proposed [20] and outperformed other rival techniques in excessive power consumption prediction. A CNN-GRU hybrid model was proposed [18] for short-term residential energy consumption prediction. In this study, two benchmark datasets, namely the AEP and IHEPC, were considered, and the proposed CNN-GRU architecture outperformed the rival machine learning and deep learning models. More recently, attention mechanism was incorporated on a CNN-BiLSTM [15] in daily load forecasting and proved effective.

The authors propose a Conv-BiLSTM model that can capture salient spatial features using a convolution operator within the LSTM cell on multiple-

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DOI: 10.1007/978-3-030-77977-1_23

dimensional data. After careful examination of the input timeseries features, the architectures of the conventional CNN and LSTM models separately, a hybrid model Conv-BiLSTM is proposed. In the hybrid Conv-BiLSTM model, both the input-to-state and state-to-state cells have convolutional structures; that is, convolutions on the input timeseries are directly inputted into each BiLSTM unit which processes the cell states in both forward and backward directions. The proposed hybrid model shows superior accuracy for building ECP because of its robust architectural structure. Most of the above-cited works using hybrid models relate mostly to residential buildings ECP. However, in this study, we consider a unique multi-functional building type marginalised used in building energy studies.

The rest of the paper is organised as follows: Section 2 introduces the proposed hybrid Conv-BiLSTM model, the rest of the forecasting methods used in this study are described in section 3, Section 4 gives a detailed description of the two case study datasets, Section 5 gives the results and discussion, and Section 6 highlights the conclusions and future works.

2 Proposed Hybrid Convolutional Bidirectional Long Short-Term Memory (Conv-BiLSTM)

Hybrid deep learning models are designed by the fusion of conventional deep learning models that combine multiple models by diversifying the input features and varying the initialisation of the weights of the neural network. The Hybrid Conv-BiLSTM model is implemented to capture the advantages of the CNN and BiLSTM techniques to improve the overall prediction accuracy. The Conv-BiLSTM is a different hybrid variant of the CNN-BiLSTM model, which does a convolution operation within the BiLSTM cells. The Conv-BiLSTM layer is a recurrent layer that replaces the usual matrix multiplication by a convolution operation. The convolution operator is applied directly to read input into the LSTM cells, that is, during the input-to-state transitions and during the state-to-state transitions [19]. The Conv-BiLSTM compresses the building energy consumption sequence into a hidden state tensor that is then decoded by an LSTM layer which processes this input in both the forward and backward directions to give the final prediction. The critical equations of the Conv-BiLSTM cell gates are given in equations 1-5;

$$I_t = \sigma(W_{XI} * X_t + W_{HI} * H_{t-1} + W_{CI} \circ C_{T-1} + b_I) \tag{1}$$

$$O_t = \sigma(W_{XO} * X_t + W_{HO} * H_{T-1} + W_{CO} \circ C_t + b_0) \tag{2}$$

$$F_t = \sigma(W_{XF} * X_t + W_{HF} * H_{t-1} + W_{CF} \circ C_{t-1} + b_F) \tag{3}$$

$$C_t = F \circ C + i_t \circ (W_{XC} * x_t + W_{HC} * h_{t-1} + b_C) \tag{4}$$

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DOI: 10.1007/978-3-030-77977-1_23

$$H_t = O \circ tanh(C_t) \tag{5}$$

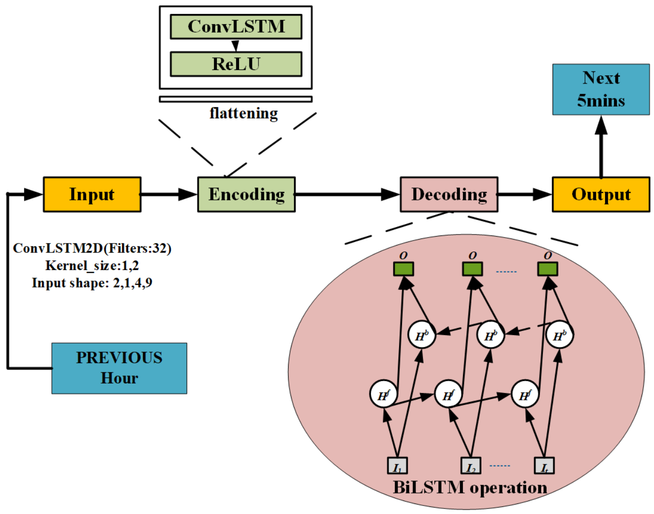

Fig. 1: An illustration of the implemented hybrid Conv-BiLSTM operational workflow.

The convolutional product and element-wise multiplication operations are denoted by "$*$" and "$\circ$" respectively. In (1-5), I_t, F_t, and O_t are the input, forget, and output gate, respectively. W represents the weight matrix, x_t is the current input data, h_{t-1} is the previously hidden output, and C_t denotes the cell state at a given timestep t. While the traditional LSTM equations use convolution operation (*), the Conv-BiLSTM instead uses matrix multiplication between W and X_t ,h_{t-1} for every gate. This matrix multiplication replaces the fully connected layer with a convolutional layer which leads to a reduced number of weight parameters in the model. The default expected input shape must be of the form [samples, timesteps, rows, columns, channels], which is similar to the form used with the image data. However, the building energy consumption timeseries data is in sequence form, which is one dimensional (1D). As such, the data is read as a row with columns. In this case, since data is in the 5-minutes interval, 60 minutes at a 5-minutes interval gives 12 columns per row. When using the Conv-BiLSTM, the previous BEC timeseries of 60 minutes is split into two subsequences of thirty minutes each (that is, two rows with six columns each), and the Conv-BiLSTM can then perform the convolutional operation on each of the two subsequences. This sequence-splitting operation results in a 5D input tensor with shape [s, 2, 1, 4, 9] denoting sample, timestep, rows, columns and channels, respectively, as shown in Figure 1. Finally, the hidden layer of the Conv-BiLSTM encoder is defined and flattened in readiness for decoding using

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DOI: 10.1007/978-3-030-77977-1_23

the traditional BiLSTM operation discussed below. The last layer is made up of the fully connected layer (dense layer), which processes the output from the BiLSTM operation.

3 Forecasting Methods

This section briefly discusses the forecasting methods adopted in this study for multi-functional buildings ECP, namely, the linear regression model, CNN model, LSTM model and BiLSTM model.

3.1 Baseline Convolutional Neural Networks(CNN)

This type of neural network was originally designed to handle image data and has achieved the state of the art results in the field of computer vision on tasks such as image classification, object recognition, among other tasks. Through representation learning, the CNN model can extract useful features automatically from timeseries data by treating a sequence of observations as a one-dimensional image. The CNN model [14] is relatively easy and faster to train because the weights are less than a fully connected architecture. In performing the ECP, a predetermined number of energy consumption historical observations are fed into the convolutional layers, which perform a one-dimensional convolution of this data. The output from the convolution operation is then passed to the fully connected layers for final processing.

3.2 Baseline Long Short-Term Memory (LSTM)

The LSTM model reads a one-time step of the sequence at a time and then builds up an internal state representation. During learning a mapping function between inputs and outputs, LSTMs, unlike MLPs and CNNs, can remember the observations seen previously and can deduce their importance to the prediction task, and since the relevant context of inputs changes dynamically, LSTM can adapt and respond appropriately [12].

3.3 Bidirectional LSTM (BiLSTM)

The LSTM is unidirectional, which has one group of hidden layers for the energy consumption sequence in the positive time directions. However, the bidirectional LSTM (BiLSTM) [19] maintains two groups by adding energy consumption input sequence in the negative time direction. The two groups of hidden layers are independent of each other, and their outputs are concatenated and linked to the same output layer. The mathematical representations describing the BiLSTM architecture are the same as that of the unidirectional LSTM except that there exist two hidden states at timestep t, that is H_t^f and H_t^f representing the forward and backward hidden states, respectively. The final hidden states representation H_t results from merging H_t^f and H_t^f is as follows [19]:

$$H_t = H_t^f + H_t^f \tag{6}$$

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4 Datasets Description

This section summaries the datasets used for developing and evaluating the different forecasting methods for ECP.

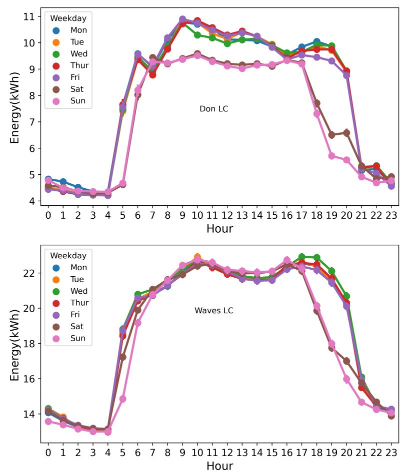

Fig. 2: An illustration of the weekday energy consumption profiles at the two leisure centres.

The datasets comprise two and half years of 5-minute resolution energy consumption observations for two leisure centres precisely, from May 2017 to December 2019. Waves leisure centre's (WLC) aggregate energy use profile is made up of 14 individual meters while Don Tatnell leisure centre's (DTLC) energy use's timeseries is a total of 5 electrical meters, all from various sections within the individual leisure centres.

Fig. 2 shows the 24-hour weekly energy consumption profiles of the two leisure centres. There is substantial similarity in the 24-hour energy use profiles between the two centres. Energy consumption rises around the 4th hour and begins dropping off at about 9 pm for most days of the week. However, on weekends, particularly on Sundays, energy consumption drops off a little earlier, between 5 pm and 6 pm for both centres.

The 5-min resolution energy consumption profiles for the two buildings demand dataset was resampled to 15 minutes, hourly datasets to test the model performances on forecasting the next step of energy consumption and facilitate merging with climatic data. The resampling was achieved through downsampling the 5min energy consumption timeseries into 15min and hourly bins and taking the sum values of the timestamps falling into a bin.

The violin plots highlighted in Figure 3 shows the observed density distribution of different electrical energy use values at the two centres. The box-plot

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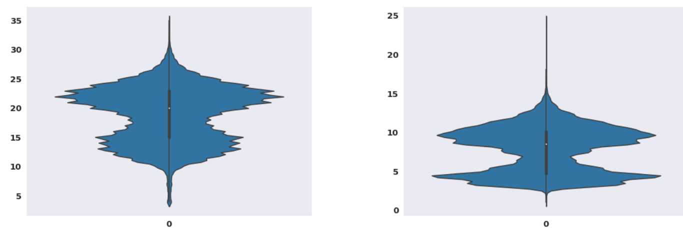
DOI: 10.1007/978-3-030-77977-1_23



(a) Waves leisure centre (b) Don Tatnell leisure centre

Fig. 3: violin plots showing the energy consumption distribution at the two centres

component (inner section) with a thick black line in the centre represents the inter-quartile ranges of the electrical energy profiles (between 15 kWh and 25 kWh) for WLC and between 4 kWh and 10 kWh for DTLC. The little white dot points at the centre represent the median electrical energy use values of 21 kWh and 9 kWh for WLC and DTLC, respectively. The long tapered top end sections show the existence of few very high energy use values at both centres. These high values were outliers from system recording errors. Any values per 5-minute interval above 35 kWh for WLC and above 19 kWh for DTLC were deemed outliers; as such, they were removed and replaced by the observation occurring immediately after (backfilling).

On the other hand, the broader section of the violin plots shows high frequency (occurrence) of electrical energy use-values. The violin plots provide a vital visual perspective that assists in data anomaly detection and designing a robust modelling process for electrical energy forecasting.

4.1 Input processing

The building energy time-series data needs to be transformed into supervised learning to allow reading by the model. The sequence data is reframed into pairs of input and output variables using the sliding window method. The inputs comprise values of the current BEC observation t and previous BEC observations at times $t-1$,$t-2$....$t-n$ which predict the output BEC observation at time $t+1$.The length of the sliding window is defined based on [11],[8].

4.2 Data Standardisation

The differences in numerical ranges between the input and output values require that the dataset be standardised. Standardisation scales each feature to have a distribution that is centred around 0, with a standard deviation of 1. Standardisation allows for comparability among input datasets, and it also enhances the training efficiency of models since the numerical condition of optimisation is

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DOI: 10.1007/978-3-030-77977-1_23

improved. The mean and standard deviation for each feature is calculated, then the feature is scaled using equation 7.

$$z = (x_i - \mu)/\sigma \tag{7}$$

where z is the standardized value, x_i is the observed energy consumption value, μ is the mean, and σ is the standard deviation of the electrical energy datasets.

4.3 Evaluation metrics

An evaluation of the models' accuracy is done using the mean absolute error MAE, root-mean-square error RMSE, and R-squared (R^2) metrics. The (R^2) metric defines the proportion of variance of the dependent variable that is explained by the regression model. A low (R^2) value closer to 0 highlights a low correlation level, while an(R^2) closer to 1 means a strong correlation exists between considered variables. The MAE metric calculates the positive mean error value for the test data. Calculating the root of the mean square error gives a metric called root-mean-square error RMSE. The RMSE penalises significant errors, which makes it a strict and reliable metric. One cannot look at these metrics in isolation in sizing up the model; rather, all the metrics must be considered at the same time. These performance evaluation metrics are calculated using equations (8-10)

$$R^2 = 1 - \frac{\sum(y - y')^2}{\sum(y - \bar{y}')^2,} \tag{8}$$

$$RMSE = \sqrt{\Sigma \frac{(y' - y)^2}{N}}, \tag{9}$$

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y' - y| \tag{10}$$

where y is the measured energy consumption value, y' is the predicted energy consumption value, and N represents the number of data pairs considered.

5 Results and discussion

This section describes the results for the next 5 minutes (mins), 15mins and hour for multi-functional buildings ECP, given the previous energy consumption observations and the calendar timestamps. The ultra-short-term to short-term forecasts are crucial for developing strategies that facilitate the safe, economical and efficient operation of multi-functional buildings. Table I and Table II show the testing phase results using the considered models for the next step energy consumption prediction for DTLC and WLC, respectively. The results of the most influential previous energy consumption values (lags) are discussed here.

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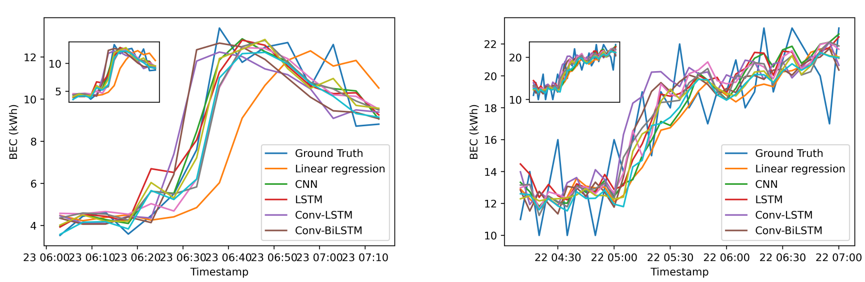
5.1 Implementation details

The data was split into 70% training, 10% validation and 20 % testing while maintaining the temporal order of the timeseries data. Temporal order maintenance, unlike random sampling, helps avoid information' leaking' into the training set; that is, it ensures no future values infiltrates the training set.

All learning algorithms were implemented in the Python programming language on google collaboratory [7] online platform. The deep learning models were built using Keras library with Tensorflow backend [10]. All development and experiments were conducted on a macOS Mojave (2.90GHz Intel Core i9 16GB 2400 MHz DDR4) machine.

5.2 Prediction using 5-minute resolution

Prediction using five-minute resolution has been chosen because it is useful in near real-time market activities such as resources dispatch and anomaly detection. The next 5min of energy consumption has been performed using the previous 25-minutes of historical energy consumption data and calendar data inputs, namely, the hour of the day, weekday or weekend, the week of the year, the month of the year, the quarter of the year, the day of the month. Fig. 4 shows extracted snapshots of the ground truth and the next 5-minutes predictions performance of the tested models at DTLC and WLC. According to the charts, the tested models do capture the trend and patterns of the ground truth line but struggle with the abrupt changes in the consumption profiles. DTLC was relatively easy to predict at this resolution, with all the tested models performing relatively well, with the R^2 score metric reaching as high as 0.87 for the deep learning models and 0.82 for the linear regression model. The proposed Conv-BiLSTM model demonstrated superior performance with RMSE, MAE and R^2 scores of 1.01 kWh, 0.76 kWh and 0.87, respectively.



(a) Don Tatnell prediction results. (b) Waves centre prediction results.

Fig. 4: An snapshort Illustration of the observed and predicted values for Don Tatnell and Waves leisure centres in the testing phase.

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Predicting the next 5-minutes of energy consumption at WLC was a relatively challenging task for the tested models with the RMSE score ranging between 2.04 kWh and 2.17 kWh and R^2 scores between 0.79 and 0.81 for the LR and the Conv-BiLSTM models, respectively. The hour of the day was influential in predicting the next 5-minutes of energy consumption at both leisure centres. Fig. 5 shows the correlations between the predicted and actual BEC values for both centers. Don Tatnell leisure centre presents are more closer fit between observed and predicted values. The existence of a large observed BEC value (45 kWh) in the test set may be responsible for degrading the correlation value between observed and predicted at this centre. Waves centre does show relative higher differences between the observed and actual values.

Table 1: Generalisation capabilities of the tested models in the testing phase for Waves leisure centre

Model	Lag	RMSE (kWh)	MAE (kWh)	R^2	Lag	RMSE (kWh)	MAE (kWh)	R^2	Lag	RMSE (kWh)	MAE (kWh)	R^2
	5min				**15min**				**1hour**			
CNN	5	2.06	1.57	0.81	4	4.34	3.21	0.9	4	14.17	9.59	0.92
LSTM	5	2.10	1.61	0.81	4	3.68	2.79	0.92	4	15.09	10.65	0.92
ConvLSTM	2,4	2.08	1.59	0.81	2,4	3.88	2.94	0.92	2,4	13.49	9.13	0.93
ConvBiLSTM	2,4	**2.05**	**1.56**	**0.81**	2,4	**3.80**	**2.86**	**0.92**	2,4	**13.00**	**8.99**	**0.94**
LR	5	2.17	1.66	0.79	4	4.62	3.29	0.88	4	18.94	12.83	0.86

5.3 Prediction using 15-minute resolution

Prediction of the next 15-minutes of energy consumption is crucial for planning effective network utilisation by energy suppliers and monitoring energy market prices. Additional features in the form of climatic variables (temperature, dew point, relative humidity, mean wind velocity and wind direction) at 15-minutes intervals were added to determine their effect on building energy consumption at the two case buildings. Prediction at 15-minutes resolution resulted in an improved prediction performance for both case buildings. The deep learning suite of models scored R^2 scores of up to 0.92, representing an improvement of up to 15% for WLC from the 5-minutes prediction scores. However, DTLC saw a marginal increase (2%) in prediction performance by the deep learning models. The proposed Conv-BiLSTM again showed superior performance by outperforming other models in both case studies with R^2 scores of 0.91 and 0.92 for DTLC and WLC, respectively. Most building energy performance studies highlight improvement in model prediction performance by use of climatic variables; however, for the two case study buildings considered in this study, the climatic variables' addition did not improve models' performances at 15-minute resolution.

5.4 Prediction using hourly resolution

This resolution represents the common choices of energy consumption prediction in building energy performance literature. All tested models did well at predict-

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DOI: 10.1007/978-3-030-77977-1_23

Table 2: Generalisation capabilities of the tested models in the testing phase for Don Tatnell leisure centre

Model	**Lag**	**RMSE (kWh)**	**MAE (kWh)**	R^2	**Lag**	**RMSE (kWh)**	**MAE (kWh)**	R^2	**Lag**	**RMSE (kWh)**	**MAE (kWh)**	R^2
	5min				**15min**				**1hour**			
CNN	4	1.05	0.80	0.86	2	2.71	2.04	0.89	4	12.74	9.58	0.84
LSTM	4	1.06	0.80	0.86	2	2.88	2.23	0.88	4	10.96	7.96	0.88
ConvLSTM	2,4	1.02	0.78	0.87	2,4	2.57	1.93	0.90	2,2	12.38	9.31	0.84
ConvBiLSTM	2,4	**1.01**	**0.76**	**0.87**	2,4	**2.54**	**1.92**	**0.91**	2,2	**10.34**	**7.56**	**0.88**
LR	4	1.18	0.89	0.82	2	3.07	2.0	0.86	4	14.05	9.93	0.79

ing the next hour of energy consumption at WLC, with the LR models scoring RMSE, MAE and R^2 values of 18.73 kWh, 12.62 kWh and 0.87, respectively. The proposed hybrid Conv-BiLSTM model continues to dominate with RMSE, MAE and R^2 scores of 13.00 kWh, 8.99 kWh and 0.94, respectively, outperforming all the other models for the WLC dataset. However, at DTLC, predicting the next hour of energy consumption was relatively challenging with superior performance from among the deep learning models scoring RMSE, MAE and R^2 values of 12.37 kWh, 9.31 kWh and 0.84, respectively. The Conv-BiLSTM model showed superior performance outperforming the popular LSTM by 6% and 5% margins in the RMSE and MAE scores, respectively.

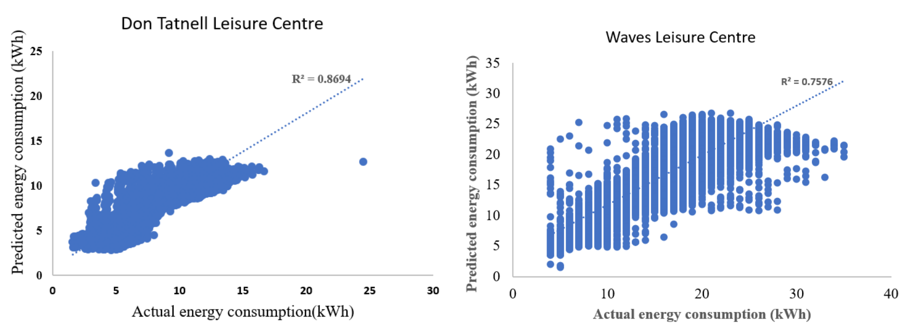

Fig. 5: An Illustration showing the correlations between the observed and predicted BEC values for the leisure centres in the testing phase.

5.5 Model Parameters

The hybrid Conv-BiLSTM architectures comprising the layer name, output shape and number of parameters for the next 5-minutes ECP at both WLC and DTLC are presented in Table 3. The proposed model had a total of 186 405 and 147 721 trainable parameters for DTLC and WLC, respectively. A dropout (20%) module was only beneficial for DTLC, while no dropout was necessary WLC as it did not improve model performance.

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DOI: 10.1007/978-3-030-77977-1_23

Table 3: Architecture of the best performing model using 5-minute resolution

DTLC Parameters

Layer (type)	Output Shape	Param #
(ConvLSTM2D_2)	(None, 1, 3, 32)	10624
(Dropout)	(None, 1, 3, 32)	0
(Flatten_2)	(None, 96)	0
(RepeatVector_2	(None, 1, 96)	0
(Bidirectional_2)	(None, 1, 200)	157600
(Dropout_2)	(None, 1, 200)	0
(TimeDistributed_4)	(None, 1, 90)	18090
(TimeDistributed_5	(None, 1, 1)	91

Total params: 186,405
Trainable params: 186,405
Non-trainable params: 0

WLC Parameters

Layer (type)	Output Shape	Param #
(ConvLSTM2D_3)	(None, 1, 1, 32)	21120
(Flatten_3)	(None, 32)	0
(RepeatVector_3)	(None, 1, 32)	0
(Bidirectional_3)	(None, 1, 200)	106400
(TimeDistributed_6)	(None, 1, 100)	20100
(TimeDistributed_7	(None, 1, 1)	101

Total params: 147,721
Trainable params: 147,721
Non-trainable params: 0

At both DTLC and WLC, the proposed Conv-BiLSTM hybrid technique showed superior non-linear mapping generalisation abilities, outperforming the baseline deep learning-based techniques. It can be concluded that the proposed hybrid Conv-BiLSTM model is effective in learning complex decision boundaries for near real-time to short term aggregate energy consumption prediction at the considered multi-functional buildings. The hybrid Conv-BiLSTM model showed satisfactory performance capturing the trends and seasonality present in the energy consumption observations as shown in Fig. 4. The proposed hybrid Conv-BiLSTM followed the electricity consumption patterns closely and performed better in predicting lower and higher electricity consumption values. This is highlighted by the closeness to the ground truth line (blue line) by the Conv-BiLSTM model line.

Predicting the ultra-short-term (5minutes) energy consumption patterns has been particularly challenging for the tested models for both case buildings studied, with the R^2 scores ranging between 0.79-0.87. The fine resolution has tendencies to bury the energy use patterns in the noise, thus making the energy use patterns invisible. However, as the resolution becomes coarser, up to the hourly resolution, the predictive performance of models increases with the proposed superior model (Conv-BiLSTM), attaining an R^2 score of 0.94 and 0.89 for WLC and DTLC, respectively. The improvement in performance as the granularity changes from 5-minutes to an hour can be attributed to the smoothening effect of the energy consumption profile, with the hourly and 15-minute resolution providing the best results for WLC and DTLC, respectively. This study demonstrates that the proposed Conv-BiLSTM is a valuable computational intelligence technique to predict energy consumption for unique multi-functional buildings.

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6 Conclusion and future works

This paper proposes a hybrid Conv-BiLSTM model for energy consumption prediction of multi-functional leisure centres. In pursuit of accurate and robust forecasting models, the hybrid Conv-BiLSTM model was tested against a suite of baseline competitive deep learning models for the next 5-minutes, 15-minutes and hour of energy consumption prediction. The results of the experiments reveal that the proposed hybrid. Conv-BiLSTM outperformed its counterpart models for multi-functional building energy consumption prediction. By directly reading the input into the LSTM cells and processing the cell states in both the forward and backward directions, the hybrid Conv-BiLSTM model was able to effectively reconstruct the energy consumption patterns at the two tested multi-functional buildings.

Multi-functional leisure centres have high and irregular energy consumption patterns than most studied building types. The study determined that for the considered building types, the previous energy consumption observations and the calendar inputs, particularly the hour of the day, had a significant effect on the energy consumption in both case buildings, and therefore the study recommends their adoption as primary inputs. The study showed that the hybrid Conv-BiLSTM model could be used for aggregate energy consumption prediction at these new building types. Ongoing work with the proposed model involves its applicability for transfer learning in which the developed model for one leisure centre (source building) will be configured to predict the other centre (target building) in an effort to curb data shortages issues in the latter.

References

1. Ahmad, M.W., Mouraud, A., Rezgui, Y., Mourshed, M.: Deep highway networks and tree-based ensemble for predicting short-term building energy consumption. Energies **11**(12), 3408 (2018)
2. Ahmad, M.W., Mourshed, M., Yuce, B., Rezgui, Y.: Computational intelligence techniques for hvac systems: A review. In: Building Simulation. vol. 9, pp. 359–398. Springer (2016)
3. Ahmad, T., Chen, H., Huang, Y.: Short-term energy prediction for district-level load management using machine learning based approaches. Energy procedia **158**, 3331–3338 (2019)
4. Almalaq, A., Zhang, J.J.: Evolutionary deep learning-based energy consumption prediction for buildings. IEEE Access **7**, 1520–1531 (2018)
5. Artuso, P., Santiangeli, A.: Energy solutions for sports facilities. International journal of hydrogen energy **33**(12), 3182–3187 (2008)
6. Berriel, R.F., Lopes, A.T., Rodrigues, A., Varejao, F.M., Oliveira-Santos, T.: Monthly energy consumption forecast: A deep learning approach. In: 2017 International Joint Conference on Neural Networks (IJCNN). pp. 4283–4290. IEEE (2017)
7. Bisong, E.: Google colaboratory. In: Building Machine Learning and Deep Learning Models on Google Cloud Platform, pp. 59–64. Springer (2019)

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DOI: 10.1007/978-3-030-77977-1_23

8. Brownlee, J.: Deep learning for time series forecasting: predict the future with MLPs, CNNs and LSTMs in Python. Machine Learning Mastery (2018)
9. Cai, M., Pipattanasomporn, M., Rahman, S.: Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques. Applied Energy **236**, 1078–1088 (2019)
10. Chollet, F., et al.: Keras documentation. keras. io **33** (2015)
11. Fan, C., Wang, J., Gang, W., Li, S.: Assessment of deep recurrent neural network-based strategies for short-term building energy predictions. Applied energy **236**, 700–710 (2019)
12. Gers, F.A., Schmidhuber, J.: Recurrent nets that time and count. In: Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium. vol. 3, pp. 189–194. IEEE (2000)
13. Kim, T.Y., Cho, S.B.: Predicting residential energy consumption using cnn-lstm neural networks. Energy **182**, 72–81 (2019)
14. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. Communications of the ACM **60**(6), 84–90 (2017)
15. Miao, K., Hua, Q., Shi, H.: Short-term load forecasting based on cnn-bilstm with bayesian optimization and attention mechanism. In: Parallel and Distributed Computing, Applications and Technologies: 21st International Conference, PDCAT 2020, Shenzhen, China, December 28–30, 2020, Proceedings 21. pp. 116–128. Springer International Publishing (2021)
16. Mocanu, E., Nguyen, P.H., Kling, W.L., Gibescu, M.: Unsupervised energy prediction in a smart grid context using reinforcement cross-building transfer learning. Energy and Buildings **116**, 646–655 (2016)
17. Rahman, A., Srikumar, V., Smith, A.D.: Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. Applied energy **212**, 372–385 (2018)
18. Sajjad, M., Khan, Z.A., Ullah, A., Hussain, T., Ullah, W., Lee, M.Y., Baik, S.W.: A novel cnn-gru-based hybrid approach for short-term residential load forecasting. IEEE Access **8**, 143759–143768 (2020)
19. Schuster, M., Paliwal, K.K.: Bidirectional recurrent neural networks. IEEE transactions on Signal Processing **45**(11), 2673–2681 (1997)
20. Ullah, F.U.M., Ullah, A., Haq, I.U., Rho, S., Baik, S.W.: Short-term prediction of residential power energy consumption via cnn and multi-layer bi-directional lstm networks. IEEE Access **8**, 123369–123380 (2019)
21. Wei, Y., Zhang, X., Shi, Y., Xia, L., Pan, S., Wu, J., Han, M., Zhao, X.: A review of data-driven approaches for prediction and classification of building energy consumption. Renewable and Sustainable Energy Reviews **82**, 1027–1047 (2018)
22. Wen, L., Zhou, K., Yang, S., Lu, X.: Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting. Energy **171**, 1053–1065 (2019)
23. Yuce, B., Li, H., Rezgui, Y., Petri, I., Jayan, B., Yang, C.: Utilizing artificial neural network to predict energy consumption and thermal comfort level: An indoor swimming pool case study. Energy and Buildings **80**, 45–56 (2014)

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DOI: 10.1007/978-3-030-77977-1_23