

## An Improved Model for Electricity Load and Price Prediction Using Hybrid Deep Learning Algorithms: A Comprehensive Review

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### ABSTRACT

Consumption of electricity is increasing in the last decade as urban areas are constantly increasing respectively. There is a growing need to bridge the gap between electricity demand and supplies which can be achieved by improving the forecast accuracy for enhanced planning. A number of techniques and computational approaches have been implored recently in order to improve prediction accuracy. However, most of the studies focus only on load forecasting with very few studies attempting to address both the load and price prediction concurrently. In order to tackle this issue, a hybrid algorithm base on Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) algorithm is proposed, which combines the advantages of (CNNs) and (LSTMs). Since CNN's feature extraction is adaptive and self-learning, the model can overcome the reliance of feature extraction and data reconstruction relying on human experience and subjective consciousness in traditional prediction algorithms (T. Liu et al., 2018). The model uses multiple convolutional kernels to scan the entire dataset to obtain relevant features and discard redundant features. Hence, our goal is to improve the prediction accuracy using a convolutional neural network (CNN) and LSTM and evaluate the model against state-of-the-art models. The research will use MATLAB as the simulation tool; and RMSE, MAE, and R2 as the evaluation metrics. The results will be compared with the existing baseline method.

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### INTRODUCTION

During the recent decade, a large number of people are tending to live in urban areas than in rural areas. The growing population of the cities wants to avail themselves of all the cutting-edge facilities that a Smart City can provide. Smart City can regulate the challenges smartly linked with increased population to control their basic integral of life, such as energy, transport, health, and homes (Fatema, Kong, & Fang, 2021). Modernization of the grid and digitization are essential to manage, monitor, and respond to the energy problems of smart cities. The sustainable development of Smart Grid (SG)

is essential for reliable and affordable electricity for smart city consumers (Fatema et al., 2021). The main issues of the modern grid include improvement in energy efficiency, integration of renewable energy sources (RESs), and reduced emission of harmful gases which are a serious threat to the environment. These issues can be tackled by using reliable and accurate information on future load demand, energy generation of RES, and suitable prices for upcoming intervals (Khalid et al., 2019).

Recently a lot of attention and effort have move towards the design and implementation of smarter grids in building in

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order to balance the demand and supply of electricity effectively (El-Hawary, 2014). Consumption of electricity is increasing in the last decade as urban areas are constantly increasing respectively (Suganthi & Samuel, 2012).. There is growing need to bridge the gap between electricity demand and supply respectively, this can be achieved by improving the forecast accuracy which will enhance planning (Singh & Dwivedi, 2018). Also a minimal improved of 1% in prediction accuracy will in turn save millions of pounds each year (Rahman, Srikumar, & Smith, 2018). Thus, Economic reasons are the main motivation behind load and price prediction (Lago, De Ridder, Vrancx, & De Schutter, 2018).

Based on this reasons among others, a number of technique and computational approaches have been implored recently in order to improve the prediction accuracy (Song, Baek, Hong, & Jang, 2005). According to (Mocanu, Nguyen, Gibescu, & Kling, 2016), electricity forecasting can be grouped into either one of these three groups, they include:

- (i) Short term forecast usually ranging from a day to a week;
- (ii) Medium term forecast usually ranging from a week to a year; and
- (iii) Long term forecast usually ranging from a year and above.

Physics base or data driven base are the main methods or approaches that is implored in the context of electricity prediction (Amasyali & El-Gohary, 2018), Stochastic model (CRBM and FCRBM) (Mocanu et al., 2016), Long Short Term Memory (Yun, Luck, Mago, & Cho, 2012), Recurrent Neural Network (Egrioglu, Yolcu, Aladag, & Bas, 2015), Elman Neural Network (Ashour & Abbas, 2018), Deep Recurrent Neural Network (Rahman et al., 2018) and Ensemble Technique (Mohammad, Chebanab, & Mohammad, 2017). Physical models can be hybridized with machine learning models to form hybrid models which have also been proposed recently, such as the study in (Fu, 2018), the Hybrid model is an empirical mode decomposition of Deep Belief Network and Ensemble Technique. In general, hybrid models have been proof to achieve high accuracy

particularly in short term forecast one hour (Qing & Niu, 2018) to one week (Iwafune, Yagita, Ikegami, & Ogimoto, 2014).

In general, electricity demand and price display distinctive features and clear correlations. Nonetheless, the electricity demand and pricing data show a few different patterns. There are different factors, such as fuel price, distribution of cheap production of the windmill and photovoltaic, social, economic, weather pattern, for such unpredicted price pattern changes. It is noticeable that just a direct change in demand does not affect the electricity price. All these aspects make electricity forecasting a challenging problem. Therefore, electricity demand and price forecasting are important for those involved in the electricity market (Fatema et al., 2021).

#### **Statement of the Problem**

Consumption of electricity is increasing in the last decade as urban areas are constantly increasing respectively. There is growing need to bridge the gap between electricity demand and supplies which can be achieved by improving the forecast accuracy for enhance planning (Abdulrahman et. al., 2021). A number of techniques and computational approaches have been implored recently in order to improve the prediction accuracy. However, most of the studies focus only on load forecasting with very few studies attempting to address both the load and price prediction concurrently (Fatema et. al., 2021). Hence, Fatema et. al., (2021) proposed electricity load and price forecasting model for sustainable smart grid using comprehensive Long Short-Term Memory (LSTM). The proposed model first takes electricity demand/price data input sequentially and then output forecast sequentially. This allows handling variable input and output length while simultaneously modelling temporal structure. However, the studies were limited by the following factors which resulted to low prediction accuracy.

- i. Multiple variables such as weather and environmental data, were not taken into consideration in the electricity demand and price

- forecasting to check the model accuracy;
- ii. Moreso, feature selection methods to select relevant features were ignored.
  - iii. Additionally, the research has no regularization approach that can improve the generalization of the model (Fatema et. al., 2021).

In order to tackle this issue, a hybrid algorithm base on Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) algorithm is proposed, which combines the advantages of (CNNs) and (LSTMs). Since CNN's feature extraction is adaptive and self-learning (Liu, Bao, Wang, & Zhang, 2018), the model can overcome the reliance of feature extraction and data reconstruction relying on human experience and subjective consciousness in traditional prediction algorithms (Liu et. al., 2018). The model uses multiple convolutional kernels to scan the entire datasets to obtain relevant features and discard redundant features. Hence, our goal is to improve the prediction accuracy using a convolutional neural network (CNN) and LSTM and evaluate the model against state-of-the-art models.

### Aim and Objectives of the Study

The aim of this study is to enhance prediction performance in the work of (Fatema et. al., 2021). The objectives of the study are to: evaluate the prediction performance of the proposed (CNN-LSTM) model using RMSE,

MAE, and  $R^2$  as the comparison metrics against the existing model.

### LITERATURE REVIEW

The overview of some basic ideas that are frequently used in relation to this planned research project are hereby presented.

#### Artificial Neural Network (ANN)

Artificial neural network is a computing intelligence that is made up neurons. It is inspired by the biological neural network. It models the complex relationship between the input and output since the neurons receives information from its input node and aggregates the information. Activation of each neuron is computed and the response is sent over output node of neurons. The traditional ANN is consisting of three main layers namely, the input, the hidden and output layers as shown in Figure 1 these layers are interconnected. Each of these layers is comprise of multiple neurons with an activation function. There is no any systematic framework for chosen the numbers of hidden layers although three categories of parameters are implored to define ANN. They include the connection style between different layers of neurons. The learning process of updating the weights of the interconnection and the activation (Wang & Srinivasan, 2016). ANN has been applied in different areas because of their human intelligence performance e.g. speech recognition, robotic control, image processing, data mining, and energy forecasting (Singh & Dwivedi, 2018).

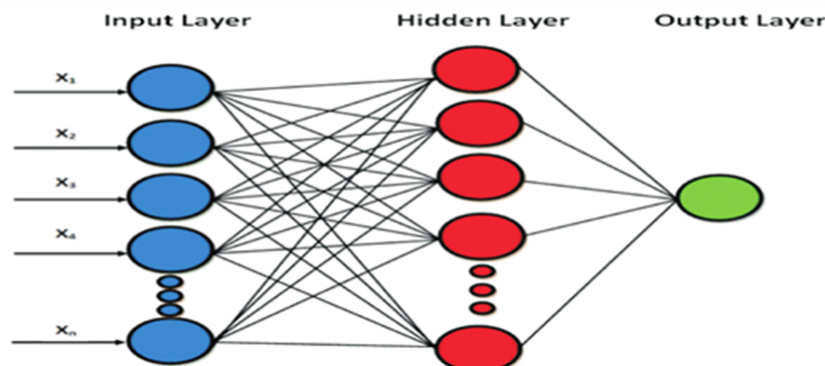


Figure 1: Structure of Artificial neural network; (Khademi & Jamal, 2016)

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### Convolutional Neural Network (CNN)

Le et al. (1998) firstly proposed Convolution neural networks (CNNs) for image processing, where spatially pooling and shared weights are the main features of the framework. CNNs were widely applied in various computer application successfully including sequential data, processing of natural language, speech recognition and image classification (Abdel-Hamid, Mohamed, Jiang & Penn, 2012). Convolutional Neural Networks mainly focus on learning features that are abstract; this is achieved by stacking and alternating pooling layers and convolution layers

respectively. This convolutional kernels which are the convolution layers in CNN convolve raw input data with multiple local filters thus producing translation invariant local features together with the subsequent pooling layers' extract features and a fixed-length over sliding windows of the raw input data in steps of several rules including average, max and other parameters according to (Zhao, Yan, Wang, & Mao, 2017). Convolutional neural network (CNN) differs from SAE and DBM in fewer parameters and no pre-training process. It replaces matrix calculation with convolution operation.

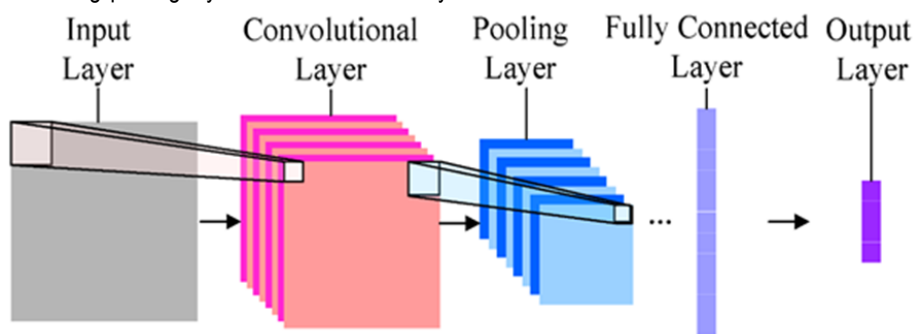


Figure 2: Architecture of convolutional neural network (Peng, Wang, Chen, & Liu, 2016).

From Figure 2 the convolution layers are the foremost layer in the CNN network. The input image maps are convolved with learnable kernels and are subsequently put through the activation function to form the output feature maps. The learning and working process of CNN can be summarized into two stages: (a) networking training and (b) feature extraction and classification. There are two parts for the first stage: a forward part and a backward part. In the forward part, the input images are fed through the network to obtain an abstract representation, which are used to compute the loss cost with regard to the given ground truth labels. Based on the loss cost, the backward part computes the gradients of each parameter of the network.

### Deep Recurrent Neural Networks Algorithms (DRNN and LSTM)

A recurrent neural network can be extended to a deep recurrent neural network via

different ways as shown by (Pascanu, Gulcehre, Cho, & Bengio, 2013), the concept of depth in RNN was initially argued, but based on the architecture of RNN, three areas can be made deeper in order to construct a DRNN, this includes; hidden to hidden function, hidden to hidden transition and hidden to output function (Pascanu et al 2014).. The idea of RNNs with gated units was first introduced by (Hochreiter & Schmidhuber, 1997). LSTM is suitable for modeling long range dependencies; LSTM's architecture has memory blocks compared to RNN which has hidden units (Chniti, Bakir, & Zaher, 2017). They memory cells which are modulated by nonlinear sigmoidal gates are contained in a memory block, which are multiplicatively applied. Memory of the same gates share cells so as to reduce the parameters, the model stores the values at the gates (when the gates evaluate to 1) or remove them (when the gates evaluate to 0) as determined by the



gates. With this, long-range temporal context can exploit by the network (Greff, Srivastava, Koutník, Steunebrink, & Schmidhuber, 2015).

In order to solve the problem of vanishing gradient during forward and backward phases, the vanishing gradient are alleviated to allow the network to preserve its memory over some time steps. If CNNs are seen as specially designed for grid data like images, recurrent neural networks (RNNs) are constructed for sequential data. However, when the traditional RNNs try to learn wind speed series with long-term dependence, the gradient tends to disappear or sometimes explode after propagation. Therefore, some scholars used gated RNNs to solve this problem, which include long short-term memory (LSTM) and gated recurrent unit (GRU). The LSTM uses memory cells to memorize the temporary state. The input gate, forget gate and output gate are used to change the information of cell state (Liu et al., 2019).

#### **Ensemble and Hybrid Techniques**

In general, combination of different approaches such as mixing physical and statistical approaches or combining short term and medium-term models, etc., is referred to as a hybrid approach. For example, radiative transfer and NN techniques are combined with Special Sensor Microwave/Imager (SSM/I) to get ocean surface wind speeds and direction. Results show that combination of NN would substantially enhance the impact of these data in NWP than just using SSM/I (Soman, Zareipour, Malik, & Mandal, 2010). Ensemble strategy, due to the diversity, the models can obtain numerous individual forecasting results. It is crucial to adopt appropriate strategies to combine the individual forecasting results. The utilized ensemble strategies in wind energy forecasting models can be classified into two types: weighted-based and learner-based. In the field of ensemble learning, simple averaging method is sometimes adopted to integrate the individual forecasting results, which assigns equal combination weights to individual predictors. Weight-based ensemble model derived from the simple averaging

method. The traditional weight-based ensemble model is a linear combination that adds up the forecasting results of  $N$  individual predictors (Liu et al., 2019).

#### **REVIEW OF RELATED EMPIRICAL STUDIES**

There are three categories and methods that are used in the prediction of building energy consumption, these include statistical method (black box models), engineering methods (white box models) and hybrid methods (grey box model) (Tardioli, Kerrigan, Oates, James, & Finn, 2015), both machine learning and statistical model have been employed in the previous works as discussed in the literature. For example, (Robinson et al., 2017) proposes a machine learning approach using natural data from CBECS to forecast both electricity, fuel and natural gas consumption of commercial building with the aid of the building features that are accessible, similarly (Deng, Fannon, & Eckelman, 2018) test various prediction models for HVAC and energy usage, an improved accuracy was demonstrated by SVM. Also in the work of Kaur and Sachin (Kaur & Ahuja, 2017) auto regressive moving average ARIMA was used to forecast electricity consumption.

Previously in the context of building energy consumption modeling, machine learning models perform better than linear models for example (Tso & Yau, 2007) test linear regression models, decision tree and neural network for electricity consumption modeling at building level in Hongkong. Similarly, (Dehalwar, Kalam, Kolhe, & Zayegh, 2016) use ANN and bagged regression tree for load prediction using data from the metrological agencies, in both cases, neural network performs better. One of the common limitations among statistical, engineering and hybrid models is the availability of vital data (Robinson et al., 2017).

Potential improvement on prediction accuracy of the aforementioned machine learning can be obtained using deep neural network where modeling of more complex functioning is allowed by the use of multiple layers of abstraction. These approaches are being applied recently in the context of energy prediction for





example (Fu, 2018) employ deep learning approach for the determination of cooling load prediction which outperforms SVM and BPNN in terms of accuracy and stability. Similarly, (Fan, Xiao, & Zhao, 2017) Propose a deep learning for building profile load predictions, an enhance performance was obtained especially when the deep neural network is use in an unsupervised manner. Recurrent neural networks are known to improve time series prediction errors as shown by (Ashour & Abbas, 2018). (Ruiz, Rueda, Cuéllar, & Pegalajar, 2018) propose an ENN and optimize the weight with GA, an improved result was obtained compare to previous studies. Similarly, (Egrioglu et al., 2015) proposed a new recurrent ANN model base on multiplicative neuron model and it was observed that the model produce the most forecast accuracy compared to other forecasting method. The work in (Hashmi, Arora, & Priolkar, 2015) have proven NARX model to forecast the future electricity demand with high accuracy requiring few number of real time parameters like weather data for accurate forecasting.

Recently, Khalid et. al., (2019) proposed Electricity Load and Price Forecasting Using Jaya-Long Short Term Memory (JLSTM) in Smart Grids. The values of the performance metrics depict that the proposed model has higher accuracy than SVM and univariate LSTM. However, feature selection methods to select relevant features were ignored. Besides this, the research has no regularization approach that can improve the generalization of the model. More recently, (Fatema et al., 2021) proposed Electricity demand and price forecasting model for sustainable smart grid using comprehensive long short term memory. Compared to SVM, RT, and NARX, the performance indices, Root Mean Square Error (RMSE) of the proposed forecasting model has been improved by 11.25%, 20%, and 33.5% respectively considering demand, and by 12.8%, 14.5%, and 47% respectively considering the price; similarly, the Mean Absolute Error (MAE) has been improved by 14%, 22.5%, and 32.5% respectively considering demand, and by 8.4%, 21% and 61% respectively considering price.

**Table1.** Summary of The summary of related work by proposed technique, compared method for evaluation, findings and weakness/limitation

Authors	Method	Evaluation Algorithms	Research Findings and Best Forecast Accuracy Achieved	Weakness and Open Issues
(Li, Hu, Liu, & Xue, 2015)	ANN	PSO-ANN and GA-ANN	PSO-ANN consume less running time with MAPE of 0.0162	Limited to a single building
(Hashmi et al., 2015)	NARX	Not available	High accuracy with few real time parameters achieving RMSE of 0.0211	Focus on short term forecasting
(Deb, Eang, Yang, & Santamouris, 2015)	ANN model	ANN and ANFIS	Both models achieved good results with R <sup>2</sup> of 0.96 and 0.958	Ignores occupancy schedule
(Platon, Dehkordi, & Martel, 2015)	CBR and ANN	ANN and CBR	ANN constantly perform better than CBR with CV(RMSE) of 7.3000	Occupancy profile was not included
(Ferlito et al., 2015)	ANN	Not available	Accuracy depends on the time horizon with best scenario of	The parameters and energy usage have no relation

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(F. Zhang, Deb, Lee, Yang, & Shah, 2016)	weighed multi – SVR	DE with SVR, SVR, PSO, and GA	RMSPE at 17.97 SVR was more accurate than compare method with MAPE of 3.4612	Accuracy may reduce with operation changes
(Dehalwar et al., 2016)	ANN	ANN, bagged regression tree	Better prediction by bagged regression tree with MAE of 1.67	Bagged regression tree converges slowly
(Nazari, Kazemi, Hashemi, Sadat, & Nazari, 2015)	GA and PSO	Linear and exponential GA and PSO	PSO exponential Model outperform GA with RMSE of 3.23121	Less accuracy compares to previous work
(Massana, Pous, Burgas, Melendez, & Colomer, 2016)	Machine Learning	SVR model, ARMA-X, MLR or ANN.	Model of SVR was the best load forecaster with MAPE of 18.0500	Prediction accuracy was less
(Buitrago & Asfour, 2017)	NARX	MLP, ARMAX, State space method	30% improvement in forecasting accuracy achieving MAE of 2.9123	Occupancy behavior not captured
(W. Zhang, Guhathakurta, Pendyala, Garikapati, & Ross, 2017)	ML models	Lasso, Linear, RF, Ada boost, Gradient boost and Elastic net	Demonstrate an exciting new approach with R of 0.908	Depends heavily on historical micro sample
(Rahman et al., 2018)	DRNN	RNN, MLP	DRNN was suitable for the prediction with RMSE of 11.8	The accuracy is subject to future weather/operations changes
(Ruiz et al., 2018)	ENN	NAR, NARX	Optimized result compares to previous studies with MSE of 0.005085	Increasing curse of dimensionality
(Robinson et al., 2017)	machine leaning	SVR, linear SVR, MLP KNN, LASSO	GB regression outperforms linear model with R <sup>2</sup> of 0.82000	There is tradeoff between data and accuracy
(Deng et al., 2018)	Machine Learning	LR, Lasso, SVM, ANN, GB	SVM predict more accurately with RMSE of 27.8	Ignores occupancy characteristics
(Alobaidi, Chebana, & Meguid, 2018)	ensemble approach	EANN, SANN and BANN	EANN was more accurate and stable with RMS of 30.4502	Higher computational time
(Banihashemi, Ding, & Wang, 2017)	Hybrid Model	Not available	Optimized and enhance prediction accuracy was achieved with MSE of 0.40974	May not be applicable to another ML algorithm
(Chniti et al.,	LSTM and	univariate and	Multivariate LSTM	Training difficulties

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2017)	SVR	multivariate SVR	obtain better accuracy with RMSE of 2.43	
(H. Wang, Wang, Li, Peng, & Liu, 2016)	DNN	ANN	The DNN model prediction was superior with RMSE of 0.5494	May not be applicable to real practice
(Yong et al., 2017)	An enhance NN	BP and NN	Prediction performance was improved with MSE 1.949	Parameters and hidden neuron need much attention
(L. Wang, Wang, Qu, & Liu, 2018)	NNsLEF	BPNN, DAN2, EANN, and ESN	NNsLEF outperforms all the models with MSE of 2.88	Computationally difficulties on larger data
(Ashour & Abbas, 2018)	ENN	ENN, ARIMA	ENN is better than ARIMA for time series with MAPE of 0.26	Training difficulties
(Skomski et al., 2020)	Transfer Learning with Hephaestus	Not Applicable	Improves energy prediction accuracy with 10% for a new building with limited data	Fail to add instance weighting method to improve the performance of Hephaestus
(Wei et al., 2019)	FFN and ELM	FFNN, ELM and Ensemble	Including occupancy data as input is able to improve the accuracy RMSE with 1.9179	It is difficult for one sensor to capture the dynamics of the entire indoor environment
(Mawson & Hughes, 2020)	DNN and RNN	FFNN and RNN	The recurrent model has accuracies of 96.82%.	A high error was obtained for prediction of indoor humidity
(Runge, Zmeureanu, & Le Cam, 2020)	ANN and ML	Ensemble Model	The optimized ANN has the lowest CV(RMSE) of 1.8%	Fail to deploy homogenous models in order to save on time development for the ML forecasting models
(Fatema et al., 2021)	long short-term memory	SVM, RT, and NARX,	the performance indices, Root Mean Square Error (RMSE) of the proposed forecasting model has been improved by 11.25%, 20%, and 33.5% respectively	multiple variables such as weather and environmental data, were not taken into consideration in the electricity demand and price forecasting to check the model accuracy

### Research Gap

A number of techniques and computational approaches have been implored recently in order to improve the prediction accuracy. However, most of the studies focus only on load forecasting with very few studies

attempting to address both the load and price prediction concurrently (Fatema et al., 2021). Hence, (Fatema et al., 2021) proposed electricity load and price forecasting model for sustainable smart grid using comprehensive Long Short-Term Memory (LSTM). The proposed model first

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takes electricity demand/price data input sequentially and then output forecast sequentially. This allows handling variable input and output length while simultaneously modelling temporal structure.

However, the studies were limited by the following factors which resulted to low prediction accuracy. Multiple variables such as weather and environmental data were not taken into consideration in the electricity demand and price forecasting to check the model accuracy; and then feature selection methods to select relevant features were ignored. Besides this, the research has no regularization approach that can improve the generalization of the model (Fatema et al., 2021).

## METHODOLOGY

### *The Proposed System*

To tackle the problem in (Fatema et al., 2021), a CNN-LSTM algorithm is proposed, which combines the advantages of convolutional neural networks (CNNs) and long short-term memory networks (LSTMs). Since CNN's feature extraction is adaptive and self-learning, our model can overcome the reliance of feature extraction and data reconstruction relying on human experience and subjective consciousness in traditional prediction algorithms. The model uses multiple convolutional kernels to scan the entire datasets to obtain relevant features and discard redundant features. Hence, our goal is to improve the prediction accuracy using a convolutional neural network (CNN) and LSTM

and evaluate the model against state-of-the-art models.

### *Analysis of the Existing System*

This existing study (Fatema et al., 2021) proposes an electricity demand and price forecast model for smart city using a LSTM model. The first processing step of the LSTM network model design begins by demanding the datasets (Energy demand and price). The electricity demand and spot pricing dataset used as a separate row vector, each contains values of the accumulated electricity demand and spot price with a 30-min resolution. A variety of random factors, such as demographic, socioeconomic or cultural, weather conditions, etc., can influence the electricity demand and price behaviour. Therefore, the accuracy of original data is sometimes low and it is necessary to pre-process the original data to improve the model prediction accuracy. The study pre-processes data through standardization. Before taking data to train the forecast model, standardize the training data to have zero mean and unit variance for a better fit, and to eliminate the training from deviating. The two datasets are demanded separately for network training after standardization. The LSTM network forecasts step forward values at each time step throughout the training process. In this scenario, electricity demand and price data are the separate input as the single time-series data to the model. The LSTM network is trained individually for these two different features. The architecture of the existing system is depicted in Figure 4.

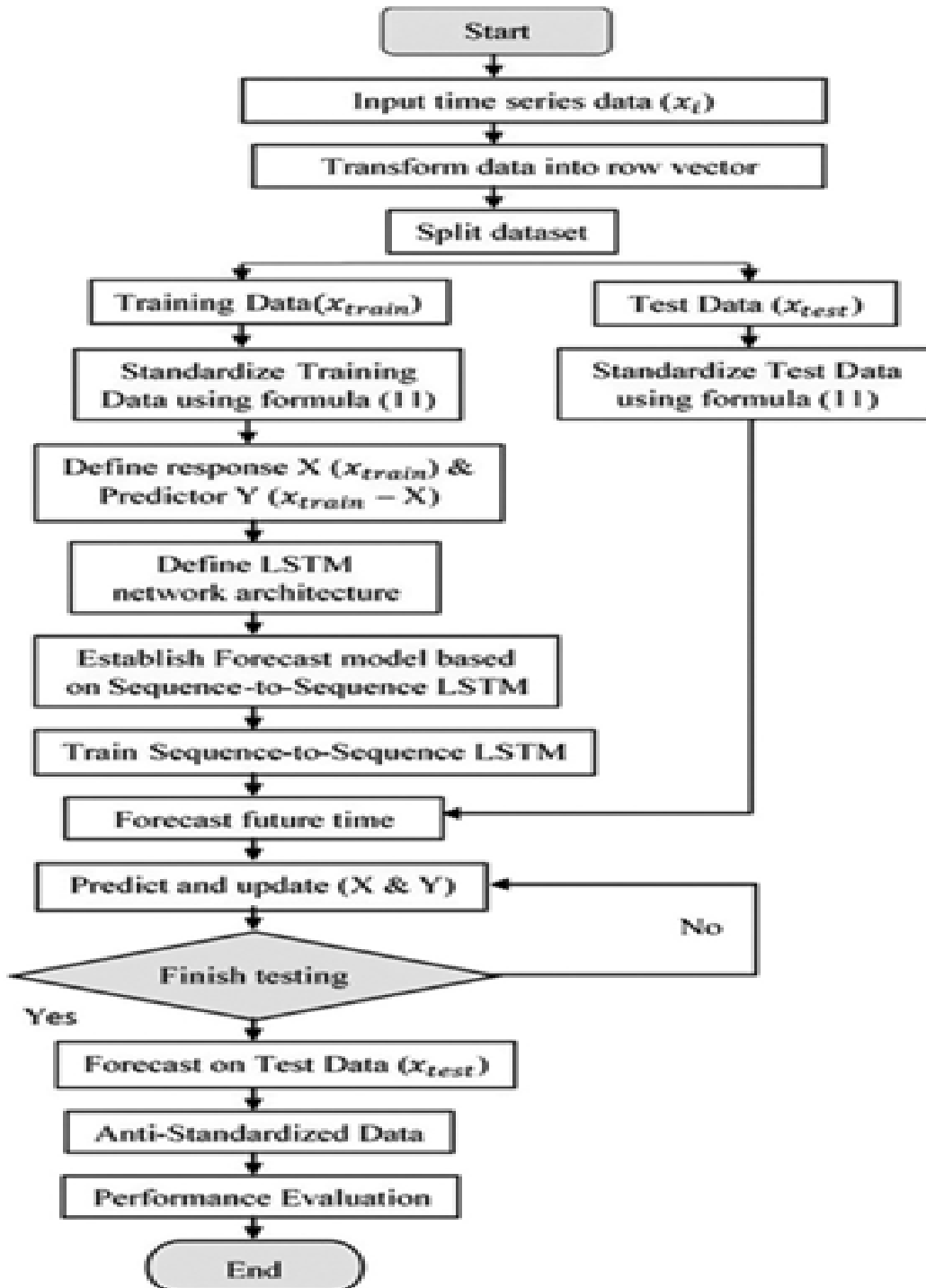


Figure 3: Framework of the existing system (Fatema et al., 2021)

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The MAE and RMSE values were used to evaluate the performance of the scenarios when comparing the observational data and predicted values made during the training and testing process

### **Weakness of the Existing System**

The studies were limited by the following factors which resulted to low prediction accuracy. Multiple variables such as weather and environmental data were not taken into consideration in the electricity demand and price forecasting to check the model accuracy; and then feature selection methods to select relevant features were ignored. Besides this, the research has no regularization approach that can improve the generalization of the model (Fatema et al., 2021).

### **Working Principle of the Proposed Model**

This research proposes to provide an improve model using hybrid CNN-LSTM model that will forecast electricity load/price and includes weather information to the prediction performance. The working of the proposed system is described in this section. Firstly, the dataset is fed as input to the CNN network which is built on the top layer of the LSTM neural network. Since CNN's feature extraction is adaptive and self-learning, our model can overcome the reliance of feature extraction and data reconstruction relying on human experience and subjective consciousness in traditional prediction algorithms. It uses multiple convolutional kernels to scan the entire data to obtain redundant features of all the load and price datasets. The feature hybrid stage, the three-dimensional feature tensor output from the last layer of CNN is firstly stretched into a one-dimensional feature vector. This vector has all feature information extracted by convolutional kernels, which includes some blank information, similar information, unnecessary information, and so on. Then the feature vector is mapped to two-dimensional space as the input of LSTM. Each row of the feature matrix is considered as a basic unit to be hybridized. Each time step reads a row of feature information and divides a feature

matrix into several time steps to read. In this way, the single process data is converted into "sequential" data in this sense. The LSTM network is used to extract the dependencies between each row of feature matrix, so as to filter and hybridize the features extracted from the CNN network. Figure 5 depict the proposed innovation.

The LSTM network is a type of Recurrent Neural Network (RNN) that can learn long-term dependencies between time steps of sequence data (Gital et al., 2019). This work adopts a sequence-to-sequence regression LSTM network architecture, in order to forecast the values of future time steps of a sequence, the network train the sequence-to-sequence regression LSTM network, where the responses are the training sequences with values shifted by one-time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step in order to accomplish the task, the electricity load/price datasets must be predicted by combining the weather information in order to curtail the uncertainty of weather affecting the future prediction thus the data is loaded to the network as a sequence data. This allows handling variable input and output length while simultaneously modelling temporal structure. Additionally, NARX techniques are used to improve LSTM model performance by incorporating exogenous factors that can affect the forecast accuracy (Gital et al., 2019). In general, it can be seen from Figure 5 that this algorithm is mainly divided into feature extraction stage based on CNN and feature fusion and prediction stage based on LSTM.

### **Choice of Metrics**

Performance measures allow the evaluation of the accuracy of various forecasting techniques useful to a particular time series. To evaluate the forecast errors, it is necessary to analyze the performance. Testing the Neural Network is a vital step in the design process. Commonly used metrics to evaluate forecast accuracy are the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and

correlation coefficient value (R2) (Kuo & Huang, 2018). A lower RMSE and MAE indicates a better forecasting result, which measures the difference between the actual values to the forecasting values. The R2 value, which is between 0 and 1 (where 0 means no correlation and 1 means the model has no error), determines the correlation between actual and predicted values. In this experiment, a Standard Statistical estimating metric was used to evaluate the network performance so as to select the model with the best performance. The developed network is tested and evaluated by using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the correlation Error (R2) in the MATLAB Neural Network (NN-tools) package. The three error measures are defined as follows:

$$RMSE(X, h) = \sqrt{\frac{1}{m} \sum_{i=1}^m (h(X^{(i)}) - y^{(i)})^2} \quad \dots 1$$

$$MAE(X, h) = \frac{1}{m} \sum_{i=1}^m |h(X^{(i)}) - y^{(i)}| \quad \dots 2$$

$$R = \frac{\sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^m (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^m (y_i - \bar{y})^2}}$$

Where considering x to be the actual values, y defining

The predicted values,  $\bar{x}$  defining mean of x,  $\bar{y}$  defining the mean of y, X is a matrix containing all the features values, h is the prediction function and m is the total number of instances in the test set

### System Specification

The system will be implemented using MATLAB version 2018a on DELL laptop System Core i (TM) i7-4200U, 1.7GHz CPU and 6GB RAM. The system is experimented using the dataset specified in the design.

### Data Collection and Preprocessing

The dataset collection stage involves the identification of predictor variables and Data collection stage. For this research, the AEMO has an open dataset, which contains

accumulated daily electricity demand (30 min MW) and price (30 min/MWh) sampling rate (AEMO 2019). The range of data for this study is 3 years, from the year 2017 January to 2019 November comprises 50,112 time-series data; and 1 year, from 2018 to 2019 November comprises 18,001 time-series data of New South Wales (NSW), Australia. In this research, the dataset is collected from the official sources and saved in the appropriate data format (.xlsx). The relevant predictor variables that are significant for the modeling of the system are identified and then selected. After identification of the relevant input variables. The Data set is pre-processed by carrying out Data cleaning and Shrubbing to eliminate typographical errors and inconsistencies in the data and saved in the format required by MATLAB through data formatting phase. We carry out data normalization scheme using the minmax (-1 to 1) to normalize the dataset for fast convergence. To improve the model performance, the min max normalization will be used to normalize the datasets for smooth application to the model. Thus, the L2 will be employed for the regularization to ensure the generalization of the model. The steps involved in the preprocessing are the splitting of the dataset into two detached groups, training, and test dataset; reserving the test data; training the remaining data set, and then use the test data set for unbiased performance comparison. The LSTM network of this research will train on the first 90% (initial network) and test on the last 10% of the time series sequence. The choice of 90 % for training will allow the deep learning model enough training data to learn the complex pattern in both the electricity load and price datasets.

### CONCLUSIONS AND FUTURE RESEARCH DIRECTION

This research can extend to enhancing the robustness of hybrid deep learning algorithms for electricity load and price prediction; thus, future work should focus on performance of hybrid deep learning models in predicting electricity load and price variations. According to the findings of this research work, none of these



models were employed, and hybrid deep learning algorithms offer enhanced accuracy and reliability in predicting electricity load and price fluctuations, showcasing their potential to significantly benefit energy management and financial decision making in the power sector.

## REFERENCES

- Abdulrahman, M. L., Ibrahim, K. M., Gital, A. Y., Zambuk, F. U., Ja'afaru, B., Yakubu, Z. I., & Ibrahim, A. (2021). A Review on Deep Learning with Focus on Deep Recurrent Neural Network for Electricity Forecasting in Residential Building. *Procedia Computer Science*, 193, 141-154.
- Alobaidi, M. H., Chebana, F., & Meguid, M. A. (2018). Robust ensemble learning framework for day-ahead forecasting of household based energy consumption. *Applied Energy*, 212, 997-1012.
- Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*, 81, 1192-1205.
- Ashour, M. A. H., & Abbas, R. A. (2018). *Improving Time Series' Forecast Errors by Using Recurrent Neural Networks*. Paper presented at the Proceedings of the 2018 7th International Conference on Software and Computer Applications.
- Banihashemi, S., Ding, G., & Wang, J. (2017). Developing a hybrid model of prediction and classification algorithms for building energy consumption. *Energy Procedia*.
- Brockwell, P. J., Davis, R. A., & Calder, M. V. (2002). *Introduction to time series and forecasting* (Vol. 2): Springer.
- Buitrago, J., & Asfour, S. (2017). Short-term forecasting of electric loads using nonlinear autoregressive artificial neural networks with exogenous vector inputs. *Energies*, 10(1), 40.
- Cadenas, E., Rivera, W., Campos-Amezcuca, R., & Cadenas, R. (2016). Wind speed forecasting using the NARX model, case: La Mata, Oaxaca, México. *Neural Computing and Applications*, 27(8), 2417-2428.
- Chniti, G., Bakir, H., & Zaher, H. (2017). *E-commerce time series forecasting using LSTM neural network and support vector regression*. Paper presented at the Proceedings of the International Conference on Big Data and Internet of Thing.
- Das, A., Annaqeeb, M. K., Azar, E., Novakovic, V., & Kjærgaard, M. B. (2020). Occupant-centric miscellaneous electric loads prediction in buildings using state-of-the-art deep learning methods. *Applied Energy*, 269, 115135.
- Deb, C., Eang, L. S., Yang, J., & Santamouris, M. (2015). Forecasting energy consumption of institutional buildings in Singapore. *Procedia Engineering*, 121, 1734-1740.
- Dehalwar, V., Kalam, A., Kolhe, M. L., & Zayegh, A. (2016). *Electricity load forecasting for Urban area using weather forecast information*. Paper presented at the 2016 IEEE International Conference on Power and Renewable Energy (ICPRE).
- Deng, H., Fannon, D., & Eckelman, M. J. (2018). Predictive modeling for US commercial building energy use: A comparison of existing statistical and machine learning algorithms using CBECs microdata. *Energy and Buildings*, 163, 34-43.
- El-Hawary, M. E. (2014). The smart grid—state-of-the-art and future trends. *Electric Power Components and Systems*, 42(3-4), 239-250.
- learning and K-shape clustering*. Paper presented at the 2017 International Joint Conference on Neural Networks (IJCNN).
- Fatema, I., Kong, X., & Fang, G. (2021). Electricity demand and price forecasting model for sustainable smart

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- grid using comprehensive long short term memory. *International Journal of Sustainable Engineering*, 14(6), 1714-1732.
- Ferlito, S., Atrigna, M., Graditi, G., De Vito, S., Salvato, M., Buonanno, A., & Di Francia, G. (2015). *Predictive models for building's energy consumption: An Artificial Neural Network (ANN) approach*. Paper presented at the 2015 xviii aistem annual conference.
- Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R., & Schmidhuber, J. Lstm: A search space odyssey. arXiv preprint arXiv: 1503. 04069, 2015. Cited on, 15.
- Hashmi, M. U., Arora, V., & Priolkar, J. G. (2015). *Hourly electric load forecasting using nonlinear autoregressive with exogenous (narx) based neural network for the state of goa, india*. Paper presented at the 2015 International Conference on Industrial Instrumentation and Control (ICIC).
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8), 1735-1780.
- Ibrahim, M., Jemei, S., Wimmer, G., & Hissel, D. (2016). Nonlinear autoregressive neural network in an energy management strategy for battery/ultra-capacitor hybrid electrical vehicles. *Electric Power Systems Research*, 136, 262-269.
- Kaur, H., & Ahuja, S. (2017). *Time series analysis and prediction of electricity consumption of health care institution using ARIMA model*. Paper presented at the Proceedings of Sixth International Conference on Soft Computing for Problem Solving.
- Khademi, F., & Jamal, S. M. (2016). Predicting the 28 days compressive strength of concrete using artificial neural network. *i-manager's Journal on Civil Engineering*, 6(2).
- Khalid, R., Javaid, N., Al-Zahrani, F. A., Aurangzeb, K., Qazi, E.-u.-H., & Ashfaq, T. (2019). Electricity load and price forecasting using Jaya-Long Short Term Memory (JLSTM) in smart grids. *Entropy*, 22(1), 10.
- Lago, J., De Ridder, F., Vrancx, P., & De Schutter, B. (2018). Forecasting day-ahead electricity prices in Europe: the importance of considering market integration. *Applied energy*, 211, 890-903.
- Li, K., Hu, C., Liu, G., & Xue, W. (2015). Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. *Energy and Buildings*, 108, 106-113.
- Liu, T., Bao, J., Wang, J., & Zhang, Y. (2018). A hybrid CNN-LSTM algorithm for online defect recognition of CO2 welding. *Sensors*, 18(12), 4369.
- Massana, J., Pous, C., Burgas, L., Melendez, J., & Colomer, J. (2016). Short-term load forecasting for non-residential buildings contrasting artificial occupancy attributes. *Energy and Buildings*, 130, 519-531.
- Mawson, V. J., & Hughes, B. R. (2020). Deep learning techniques for energy forecasting and condition monitoring in the manufacturing sector. *Energy and Buildings*, 217, 109966.
- Mocanu, E., Nguyen, P. H., Gibescu, M., & Kling, W. L. (2016). Deep learning for estimating building energy consumption. *Sustainable Energy, Grids and Networks*, 6, 91-99.
- Nazari, H., Kazemi, A., Hashemi, M.-H., Sadat, M. M., & Nazari, M. (2015). Evaluating the performance of genetic and particle swarm optimization algorithms to select an appropriate scenario for forecasting energy demand using economic indicators: residential and commercial sectors of Iran. *International Journal of Energy and Environmental Engineering*, 6(4), 345-355.
- Pascanu, R., Gulcehre, C., Cho, K., & Bengio, Y. (2013). How to construct deep

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- recurrent neural networks. *arXiv preprint arXiv:1312.6026*.
- Peng, M., Wang, C., Chen, T., & Liu, G. (2016). Nirfacenet: A convolutional neural network for near-infrared face identification. *Information*, 7(4), 61.
- Platon, R., Dehkordi, V. R., & Martel, J. (2015). Hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis. *Energy and Buildings*, 92, 10-18.
- Qing, X., & Niu, Y. (2018). Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. *Energy*, 148, 461-468.
- Robinson, C., Dilkina, B., Hubbs, J., Zhang, W., Guhathakurta, S., Brown, M. A., & Pendyala, R. M. (2017). Machine learning approaches for estimating commercial building energy consumption. *Applied Energy*, 208, 889-904.
- Ruiz, L. G. B., Rueda, R., Cuéllar, M. P., & Pegalajar, M. (2018). Energy consumption forecasting based on Elman neural networks with evolutive optimization. *Expert Systems with Applications*, 92, 380-389.
- Runge, J., Zmeureanu, R., & Le Cam, M. (2020). Hybrid short-term forecasting of the electric demand of supply fans using machine learning. *Journal of Building Engineering*, 29, 101144.
- Singh, P., & Dwivedi, P. (2018). Integration of new evolutionary approach with artificial neural network for solving short term load forecast problem. *Applied energy*, 217, 537-549.
- Skomski, E., Lee, J.-Y., Kim, W., Chandan, V., Katipamula, S., & Hutchinson, B. (2020). Sequence-to-sequence neural networks for short-term electrical load forecasting in commercial office buildings. *Energy and Buildings*, 226, 110350.
- Soman, S. S., Zareipour, H., Malik, O., & Mandal, P. (2010). *A review of wind power and wind speed forecasting methods with different time horizons*. Paper presented at the North American Power Symposium 2010.
- Song, K.-B., Baek, Y.-S., Hong, D. H., & Jang, G. (2005). Short-term load forecasting for the holidays using fuzzy linear regression method. *IEEE transactions on power systems*, 20(1), 96-101.
- Suganthi, L., & Samuel, A. A. (2012). Energy models for demand forecasting—A review. *Renewable and Sustainable Energy Reviews*, 16(2), 1223-1240.
- Tardioli, G., Kerrigan, R., Oates, M., James, O. D., & Finn, D. (2015). Data driven approaches for prediction of building energy consumption at urban level. *Energy Procedia*, 78, 3378-3383.
- Tso, G. K., & Yau, K. K. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, 32(9), 1761-1768.
- Wang, H., Wang, G., Li, G., Peng, J., & Liu, Y. (2016). Deep belief network based deterministic and probabilistic wind speed forecasting approach. *Applied Energy*, 182, 80-93.
- Wang, L., Wang, Z., Qu, H., & Liu, S. (2018). Optimal forecast combination based on neural networks for time series forecasting. *Applied Soft Computing*, 66, 1-17.
- Wei, Y., Xia, L., Pan, S., Wu, J., Zhang, X., Han, M., . . . Li, Q. (2019). Prediction of occupancy level and energy consumption in office building using blind system identification and neural networks. *Applied Energy*, 240, 276-294.
- Yong, B., Xu, Z., Shen, J., Chen, H., Tian, Y., & Zhou, Q. (2017). *Neural network model with Monte Carlo algorithm for electricity demand forecasting in Queensland*. Paper presented at the Proceedings of the Australasian

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- Computer Science Week  
Multiconference.
- Yun, K., Luck, R., Mago, P. J., & Cho, H. (2012). Building hourly thermal load prediction using an indexed ARX model. *Energy and Buildings*, 54, 225-233.
- Zhang, F., Deb, C., Lee, S. E., Yang, J., & Shah, K. W. (2016). Time series forecasting for building energy consumption using weighted Support Vector Regression with differential evolution optimization technique. *Energy and Buildings*, 126, 94-103.
- Zhang, W., Guhathakurta, S., Pendyala, R., Garikapati, V., & Ross, C. (2017). A Generalizable Method for Estimating Household Energy by Neighborhoods in US Urban Regions. *Energy Procedia*, 143, 859-864.
- Zhao, R., Yan, R., Wang, J., & Mao, K. (2017). Learning to monitor machine health with convolutional bi-directional LSTM networks. *Sensors*, 17(2), 273.

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