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A Novel Machine Learning Technique Using CNN to Forecast Power consumption Forecasting using Machine Learning Technique

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Forecasting of power demand plays an essential role in the electric industry, as it provides the basis for making decisions in power system planning and operation. Forecasting electricity consumption has major importance in the energy planning of the developing countries. In such a dynamic environment, ordinary forecasting techniques are not sufficient, and more sophisticated methods are needed. In energy usage forecasting, several new approaches are used to reliably forecast the potential demands for electricity consumption. In this paper, Machine Learning-Convolution Neural Network based power consumption prediction is proposed. With improved methods and algorithms, Machine Learning is constantly developing. The future could instantly be more effective when extended to the energy sector. The dataset is converted to a simply "trained" machine learning algorithm that enables us to forecast or

approximate the energy usage of devices or loads in the future accurately.
Keywords: electricity consumption, Machine Learning-Convolution Neural Network.

1. Introduction

In energy system, energy consumption is the important topic. Estimating long-term energy consumption is the core of energy investment planning and plays a critical role for authorities in developed countries. Therefore, in order to prevent expensive failures, modelling energy usage with reasonable precision becomes important.Based on market conditions prevailing, electricity forecasting models are established unique to a nation or utility. Each nation, under its own requirements, has a particular consumption model. In order to correctly model the consumption of energy, a few essential points must be considered. The criteria affecting the country's electricity use should, first, be well established. The second factor is to select an approach that is fitting for the model of consumption.In different fields, the most common ones use machine learning (ML) because they are helpful and the way ML functions is like a feature that better maps the input data to output. Machine learning (ML) is one of the rising scientific areas in which computer science and analytics are combined. Machine learning models can make highly accurate predictions of energy consumption. So they can be used by governments to implement energy-saving policies.The Convolutional Neural Network is used for predicting the energy consumption which predicts with high accuracy compared to other models. The CNN has different layers and each layers performs various process such as feature extraction, prediction.

1.1 Benefits of Predicting Energy Consumption:

Economic: Individuals and companies will turn electricity into costs and thus estimate and make choices on the basis of their energy bill. Practical: By not only learning how much energy we use, but also realising how and why we can, we will change our behaviours without impacting our efficiency or the quality of our lives.Technical: Improved energy data processing opens up new opportunities in the storage and interpretation of these data as well as in the generation of more reliable prediction.

2. Literature Survey

Bourhnane et al [1] investigated Artificial Neural Networks (ANN) along with Genetic Algorithms. They deployed their models in a real-world SB testbed. We used CompactRIO for ANN implementation. The proposed models are trained and validated using real-world data collected from a PV installation along with SB electrical appliances.

Mosavi et al [2] reviews the machine learning models used in the general application of energy consumption. The most important literature in the field is categorised by a novel search and taxonomy according to the ML modelling methodology, energy type, perdition type, and implementation area. In addition, this paper draws a hypothesis on the pattern and the usefulness of the ML models.

P. W. Khan and Y. C. Byun [3] proposed an approach that uses an ensemble machine learning model based on XGBoost, support vector regressor (SVR), and K-nearest neighbors (KNN) regressor algorithms. Using Jeju island's electricity consumption data as a case study shows that the proposed ensemble model optimized with GA is more accurate than the individual machine learning models.

Hyeon et al [4] predicted the household electric energy consumption using deep learning models, known to be suitable for dealing with time-series data. Specifically, vanilla long short-term memory (LSTM), sequence to sequence, and sequence to sequence with attention mechanism are used to predict the electric energy consumption in the household. As a result, the vanilla LSTM shows the best performance on the root-mean-square error metric.

Cheng et al[5] suggested a novel PowerNet neural network architecture that can integrate several heterogeneous features for the demand prediction mission, such as , weather data, historical energy usage data and calendar information. A detailed assessment was carried out using the real-world smart metre dataset to illustrate the benefits of PowerNet over proposed machine learning techniques such as Support Vector Regression (SVR), Gradient Boosting Tree (GBT), Gated Recurrent Unit (GBT) (GRU). (GRU). And Tree Random (RF).

Shan et al [6] proposed an ensemble forecast called the gravity gated recurrent electricity consumption unit model, combining the gated recurrent unit model and the proposed gravity model of logarithmic electricity consumption. Average reciprocal knowledge and weighted entropy are used to derive the weights. In terms of precision, stability, and generalisation, this method outperforms other benchmarks.

Wang et al [7] a novel enhanced integration model (stacking model) was proposed that can be used to predict the consumption of building electricity. The stacking model integrates the benefits of various base prediction algorithms and shapes them into "meta-features" to ensure that datasets from different spatial and structural angles can be observed by the final model. Two cases are used to illustrate the stacking model's realistic engineering implementations.

Kalimoldayev et al [8,9] reviewed the modern methods of forming a mathematical model of power systems and the development of an intelligent information system for monitoring electricity consumption. The main disadvantages and advantages of the existing modeling approaches, as well as their applicability to the energy systems of Ukraine and Kazakhstan are identified. The main factors that affect the dynamics of energy consumption are identified.

Wahid et al [10] used Random Tree and Multi-layer perceptron to distinguish residential buildings according to their energy consumption. Two types of buildings have been projected to absorb hourly historical data: high power and low power consumption buildings. The prediction consists of three phases: extraction of features, retrieval of data, and prediction. The hourly data consumed on a regular basis is extracted from the database in the data retrieval stage.

Rahman et al [11] presented a recurrent neural network model to make medium-to-long term predictions, i.e. time horizon of ≥ 1 week, of electricity consumption profiles in commercial and residential buildings at one-hour resolution. Residential and commercial buildings are responsible for a significant fraction of the overall energy consumption in the U.S. The proposed models were used to predict hourly electricity consumption.

3. Methodology

ML-CNN based ECP

The model consists of Power Distributor, Consumer, and SCADA Database. The CNN model consists of three layers such as convolution layer, pooling layer, fully connected layer.

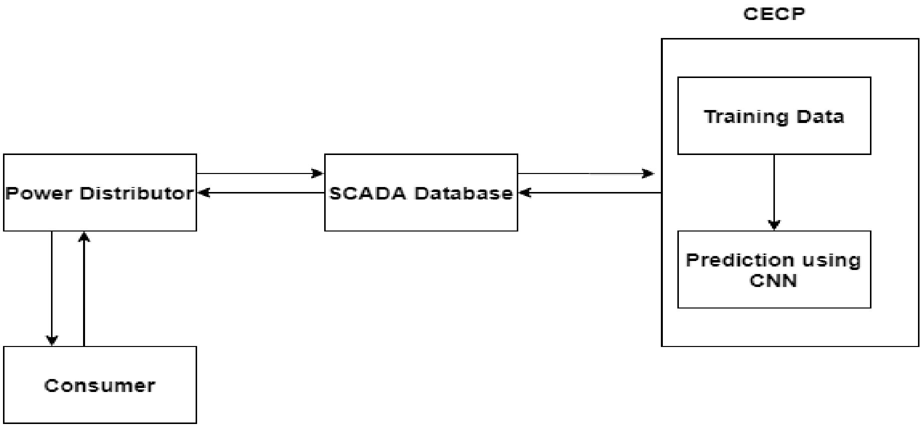

Figure 1- ML-CNN based ECP model

3.1 Power distributor

Electric power distribution is the final stage in the delivery of electric power; it carries electricity from the transmission system to individual consumers. Often several customers are supplied from one transformer through secondary distribution lines. The high voltage transmission system links the generators to substations, which supply power to the user through the distribution system.

3.2 Power Consumer

The consumption of electricity is a type of energy consumption that uses electrical energy. Electricity consumption is the real demand for energy produced by the current supply of electricity. To produce the desired output, electrical and electronic equipment consume electric power.

3.3 SCADA Database

Supervisory control and data acquisition (SCADA) is a control system architecture comprising computers, networked data communications and graphical user interfaces (GUI) for high-level process supervisory management, while also comprising other peripheral devices like programmable logic controllers (PLC) and discrete proportional-integral-derivative (PID) controllers to interface with process plant or machinery. This database contains the power distributor and power consumer.

3.4 Training data

The training data is an initial set of data used to help a program understand how to apply technologies like neural networks to learn and produce sophisticated results. The data are collected from the SCADA database to train the data for predicting the energy consumption prediction.

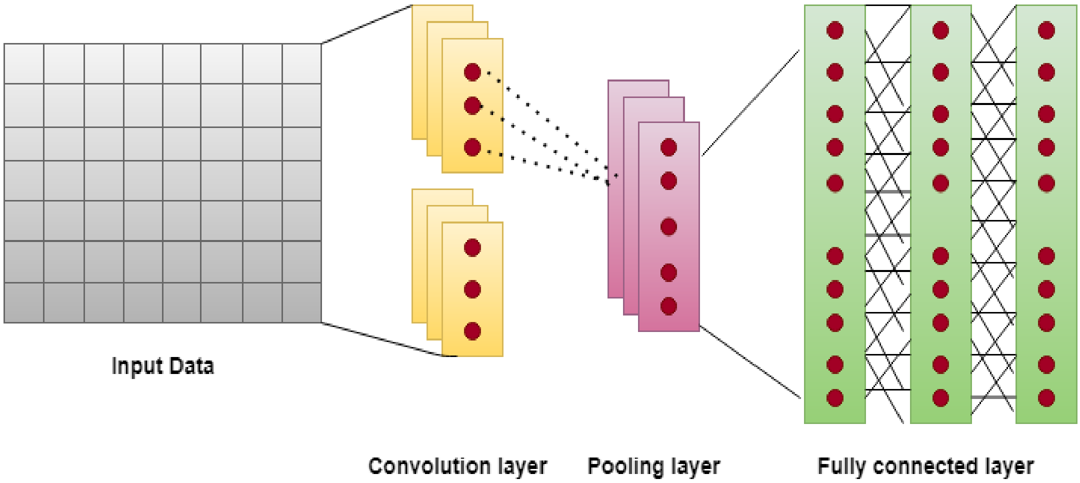

Figure 2- Architecture of CNN

3.5 Convolution Layer

Convolutional layers are the major building blocks used in convolutional neural networks. The convolutional layer is supposed to do the convolution operation on the data. Input could be considered as a function, filter applied to that is another function and convolution operation is an algorithm used to measure changes caused by applying a filter on the input. Each filter utilizes a shared set of weights to perform the convolutional operation.

3.6 Pooling Layer

Pooling layer is responsible for subsampling the data. This operation, not only reduces the computational cost of the learning process, but also is a way of handling the overfitting problem in CNN. It has a connection to the number of parameters that are learned and the amount of data that the prediction model is learned from.

3.7 Fully Connected Layer

At the final layers of a CNN, there is a MLP network which is called its fully connected layer. It is responsible for converting extracted features in the previous layers to the final output. The first fully connected layer takes the inputs from the feature analysis and applies weights to predict the correct label.

4. Result and Discussion

The following table shows the accuracy of different methods. To evaluate the performance of proposed ML-CNN based Energy Consumption Prediction method, we compare the accuracy of different algorithms.

Table 1- Accuracy of algorithms

Algorithms	Accuracy
CNN	92
LSTM	89
CNN+LSTM	85

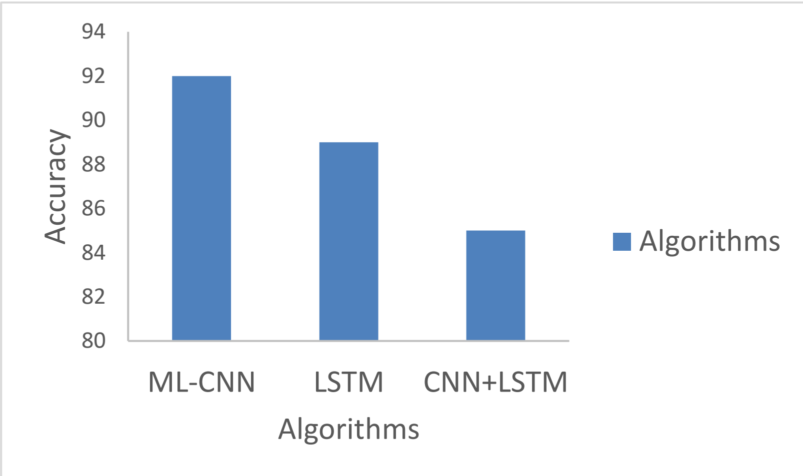

Figure 3- comparison of accuracy percentage of algorithms.

Table 2- Error Rate comparison

Error Rate	Algorithms		
	ML-CNN	LSTM	CNN+LSTM
MSE	0.009	0.05	0.07
MAE	0.06	0.08	0.12
RMSE	0.05	0.12	0.15

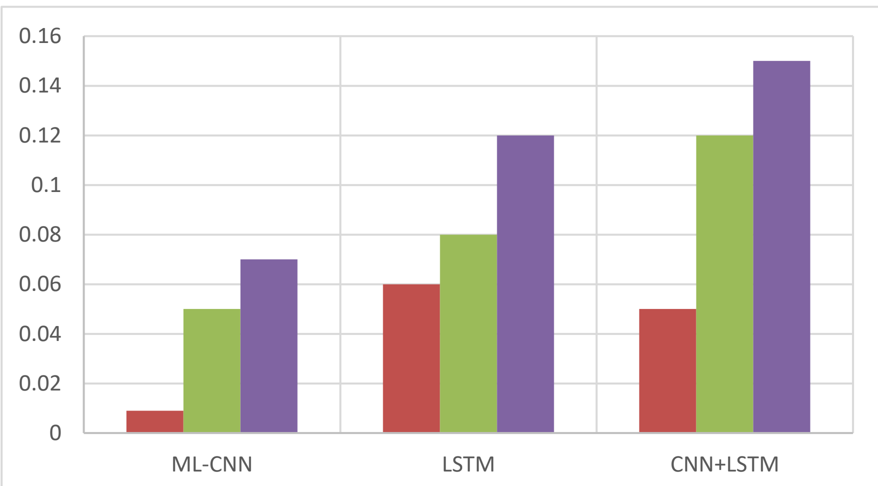

Figure 4-compariso of error rate of CNN, LSTM and CNN+LSTM.

5. Conclusion

In this paper, Machine Learning-Convolution Neural Network based power consumption prediction is proposed. With improved methods and algorithms, Machine Learning is constantly developing. The future could instantly be more effective when extended to the energy sector. The accuracy of proposed technique is 92% and in terms of multiple efficiency parameters, such as MSE, MAE, and RMSE, the proposed model's experimental results outperform other modern energy consumption forecast models.

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