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Short-Term Load Forecasting Using a Parallel CNN-BPNN Prediction Model with COVID-19 Pandemic Restriction as an Added Input Parameter and ReLU Activation Function

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Abstract. Short-term load forecasting provides a vital tool for the power system. This study delved into applying a hybridized machine learning algorithm to improve load forecasting accuracy. It aims to investigate the accuracy of the parallel CNN-BPNN prediction model in short-term load forecasting with Philippine pandemic restriction as an added parameter and a ReLU activation function. The CNN, BPNN, and the proposed parallel CNN-BPNN models were implemented using Python. They were trained, validated, and tested using the input parameters such as historical power demand, day of weeks/ Holidays, meteorological data such as temperature, wind speed, humidity, and COVID-19 pandemic restriction. The accuracy of the three models was tested using the MAPE. Results showed that the proposed model achieved the lowest MAPE of 3.52 %, lower than that of the CNN, 4.62%, and BPNN, 3.98%. Furthermore, Pearson correlation analysis showed that the relationship between electricity usage and mobility constraints is moderately correlated with a correlation value of -0.57.

Keywords: short-term load forecasting, covid-19 pandemic, convolutional neural network, backpropagation neural network, activation function

1. Introduction

The essential responsibility of any electric power business is to offer electric energy cost-effectively and securely while preserving quality. Generation, transmission, and distribution utilities all need a way to estimate electric demand to use their infrastructure efficiently, safely, and affordably. During the pandemic time of 2020, many governments worldwide imposed various levels of restrictions to stem the spread of the COVID-19 virus. In the Philippines, adopting the community quarantine in Metro Manila has affected different commercial and socioeconomic sectors, including electricity usage, due to people's reduced mobility. Several studies [1-3][10] conducted electric load forecasting, considering the COVID-19 pandemic restriction as one of the predictors to see the said restriction's impact on the forecasting accuracy.

Previous studies [8-9] dealt with the SLTF using Hybridized Naive Bayes Algorithm to enhance accuracy with Mean Square Error (MSE) of 34.35 and Mean Average Percentage Error (MAPE) of 4.41 % and investigated the potential of neural networks for SLTF, with an MSE of 9.7495. The authors of [4] proposed a series GRU-CNN to improve the accuracy of their forecasting model.

To address the accuracy concern of SLTF during the COVID-19 pandemic, one study [1] used Kalman filter with fine-tuning and transfer learning with GAM as the error data but did not try to compare result using any neural network. In the study of Alasali et al. [2], they developed an ARIMAX model by considering the non-smooth nature of demand due to the COVID-19 impact but did not include meteorological data as one of the input parameters. Another paper [3] applied the convolutional neural network (CNN) and used the COVID-19 constraint as one of the input parameters but did not try to hybridize the model with Back-Propagation Neural Network (BPNN). Therefore, it is worthwhile to conduct a study to verify the performance of a parallel CNN-BPNN model in short-term load forecasting with COVID-19 pandemic restriction as an added input parameter.

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The study's main objective is to apply a parallel CNN-BPNN algorithm in short-term load forecasting with a Philippines pandemic restriction as an added input parameter and ReLU activation function. The specific aims are to gather and acquire data, including the COVID-19 pandemic community restriction, historical power demand data, meteorological data such as temperature, wind, and humidity, and a day of the week/holiday, develop, train, and validate the CNN, BPNN and proposed parallel CNN-BPNN model, test the MAPE of the CNN, BPNN and proposed parallel CNN-BPNN load forecasting model, and compare the performance of the parallel CNN-BPNN with that of CNN and BPNN.

The study utilizes data on an hourly basis in the vicinity of Metro Manila, Philippines. It compares the performances of the proposed parallel CNN-BPNN, CNN, and BPNN models. The algorithms covered in this study were implemented using the Python programming language.

2. Proposed Model of Parallel CNN-BPNN

The neural network model proposed in this study is the parallel CNN-BPNN shown in Fig. 1. According to [6], the main benefit of using parallelism in deep learning is improving training time and explaining the importance of acceleration due to intensive processes that usually consume a lot of time.

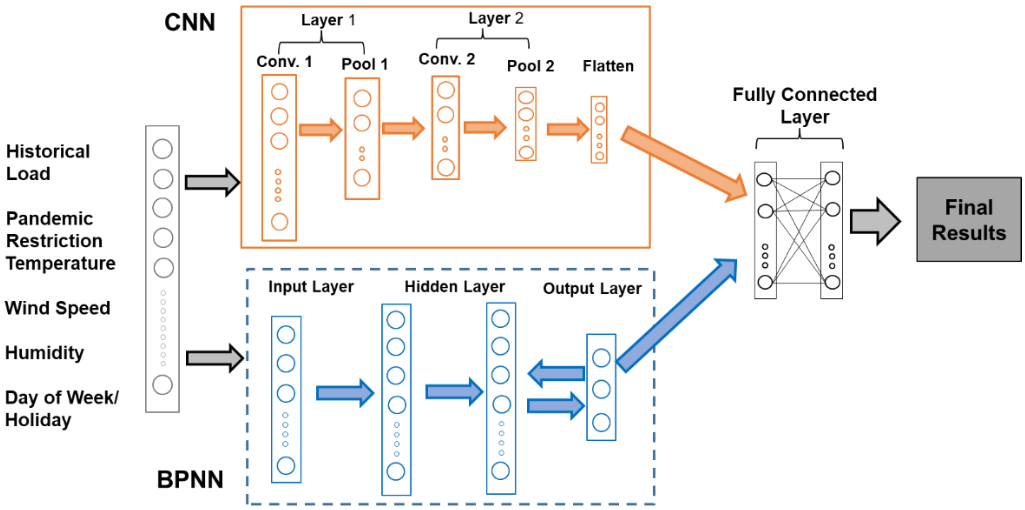


Fig 1: Architectural proposed model parallel CNN-BPNN

The first model in the parallel is the CNN, a widely adapted algorithm to address STLF and provides operational tools for solving various power system problems [3][7]. The CNN model in time series can provide efficient results when predicting short-term load forecasting. It calculates the predicted value using equation 1 below.

$$s = (x * w), \tag{1}$$

Where s is the new data, the input is denoted by x and the weight function by w. The operation is defined as a feature map with one-dimensional (1D) for the output layer. CNN comprises three components, convolutional, pooling, and dense layers. The pooling function lowers the time series data's dimensionality, reducing the network's training time and requiring down-sampling. The output data of layer two for this study were flattened and passed to the connected layer as the output result.

The second model in the parallel is the BPNN [4], known for its high generalization capabilities. It comprises the input, hidden, and output layers. Its training process uses the principle of backpropagation, and the learning method uses the gradient descent method. BPNN is used to fine-tune and refine weights based on the error level recorded in the previous epoch. Input the weights' parameters assigned randomly to any value based on the train selection.

3. Methodology

The research framework shown in Fig. 2 outlines the phases of the study, from the gathering of data down to the evaluation of results. The study comprises three phases: the gathering and preparing data, developing the forecasting model, and evaluation of the three models. The data processing included the selection of suitable parameters and taking the data from reliable sources. The data starts from January 01, 2019, and ends on December 31, 2021, where the COVID-19 pandemic was dominantly active.

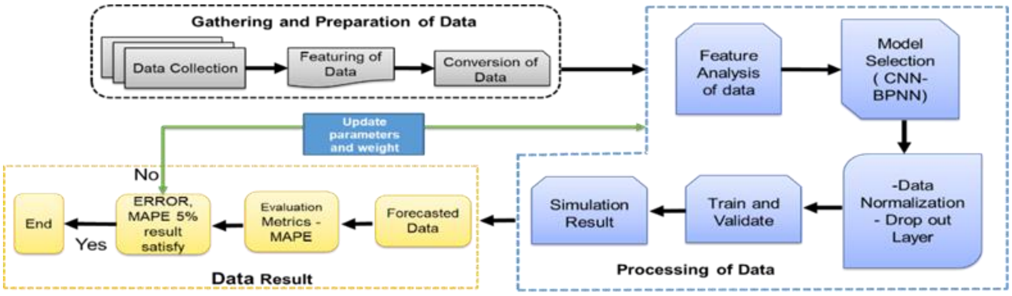


Fig. 2: Conceptual framework of the study

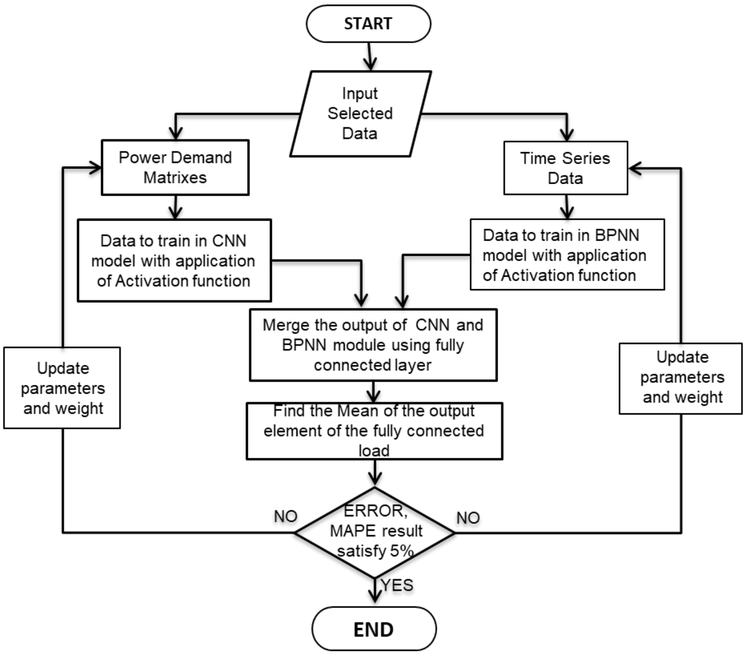


Fig. 3: Process flow of the parallel CNN-BPNN

The data was split into 70% for training, 20% for validation, and 10% for testing in chronological order, yielding 18,340, 5,260, and 2,561 inputs. Each training run is set to 1000 epochs, then save the model with the best validation MAPE. The input data arrange into a 2D matrix, and the process produced features the size of a 72x11 matrix. This study uses one-hot encoding [3] for the COVID-19 pandemic and cyclical features encoding for a day of the week to process data to a usable format. The data used normalization in the mean and variance of the training set [5]. This study used the Rectified Linear Units (ReLU) for its activation function described in equation 2 below.

$$f(x) = \begin{cases} 0, & for \quad x < 0 \\ x, & for \quad x \geq 0 \end{cases} \tag{2}$$

The accuracies of the three models are measured in MAPE given in equation 3 below:

$$MAPE = \frac{1}{N} \sum_{1}^{n} \left| \frac{y - \hat{y}}{y} \right| \; 100 \tag{3}$$

where n represents the number of tests or samples, while ŷ is the forecasted value, and y is the actual value. Performances of the models were then compared using a t-Test.

4. Results and Analysis

The accuracy of the proposed model is demonstrated in this section, which performs the model, trained, validated, and measured prediction error, MAPE. The study begins by examining the correlation of the new parameter of COVID-19 restriction community quarantine to power load demand. The statistical tool helps the Pearson correlation coefficient (r) help to understand the level of correlation. The coefficient correlation r value can range from -1 to +1, and the 0 is defined as there is no correlation.

To see the strength of the relation between COVID-19 pandemic restriction and load demand, a correlation study was conducted using the data from March 2020 to August 2020, where the highest level of restriction was implemented between these dates. Table 1 shows the result of the study with a correlation value of r = -0.57, reflected in Fig. 4, which means that the correlation between the two variables is moderate level.

Table 1: Result of correlation

Correlation Subject	Actual Power Consumption	Community Quarantine Restriction
Actual Power Consumption	1	
Community Quarantine Restriction	-0.57	1

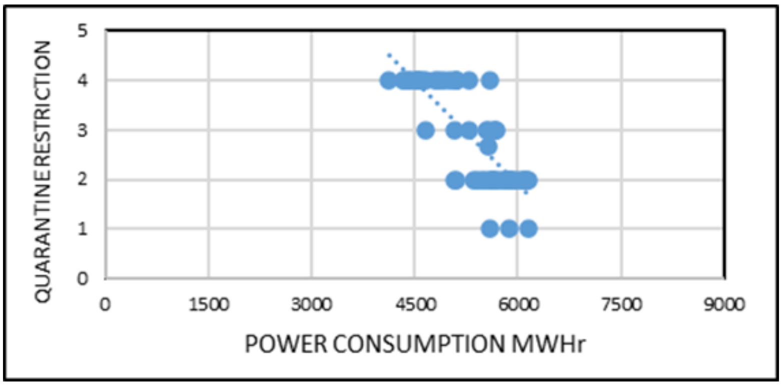


Fig 4: Correlation of power consumption to community quarantine restriction

The rate of attaining the target MAPE of the parallel CNN-BPNN model compared with the other two models is shown in Fig. 5. The lowest time record is in Test 8 with 480 seconds for the proposed model, while the highest is 3873 seconds for the BPNN model. The result proved the consistency of the parallel CNN-BPNN in its rate of attaining the target MAPE.

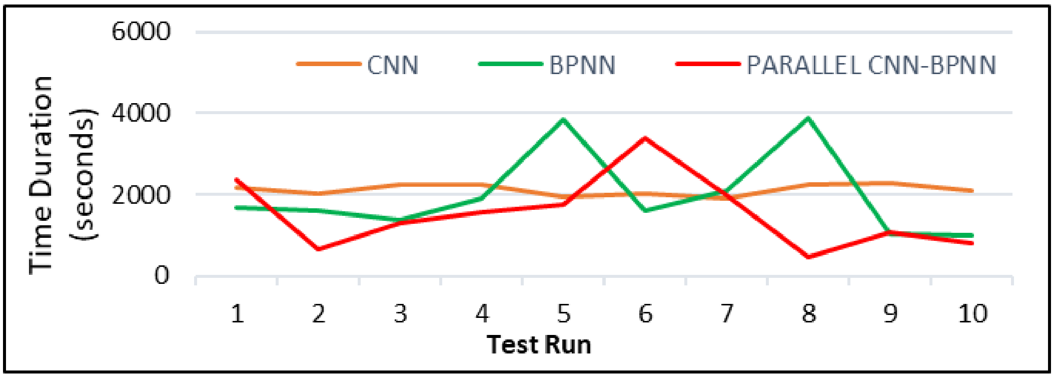
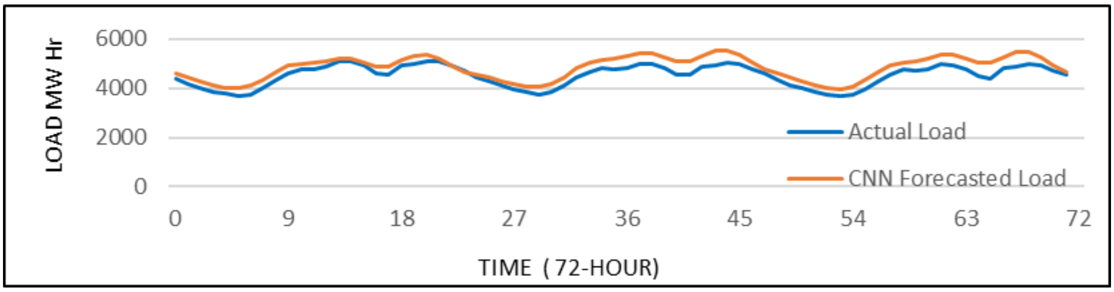


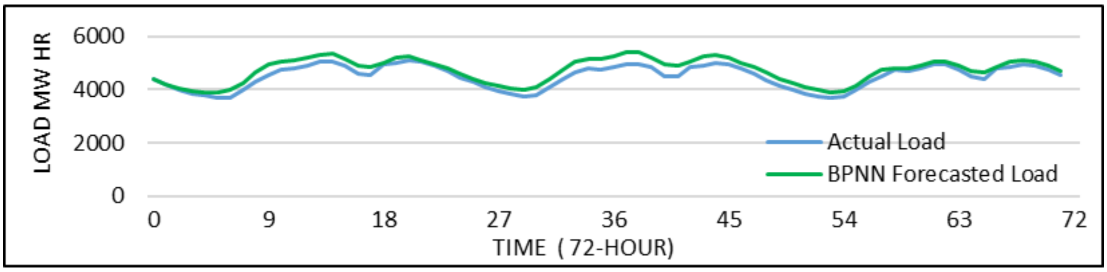
Fig. 5: Data validation time duration of CNN, BPNN, and parallel CNN-BPNN model

Figure 6 exhibits a sample forecast of the model for the first 72-hour testing compared to the actual data. Figure 6a reveals that the CNN model produced a large deviation gap in the middle of the test, while the BPNN, in Figure 6b, improved its deviation from the actual load, which indicates that this model is better than CNN. Figure 6c shows that the proposed parallel model has minimal variation from the actual data. Parallel CNN-BPNN produced the most accurate forecast of all the three compared models, as shown in Figure 6d.

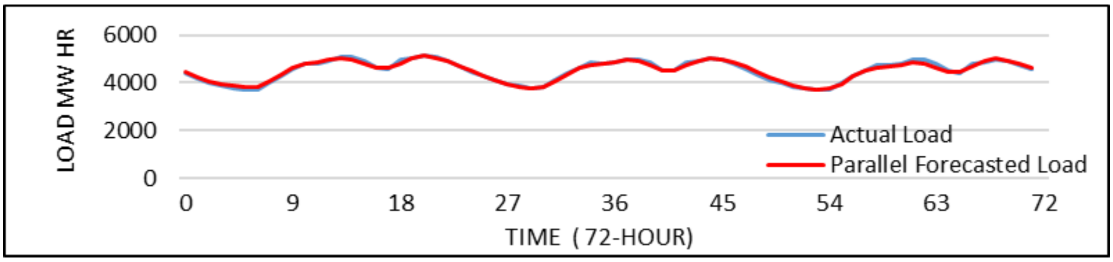
(a)



(b)



(c)



(d)

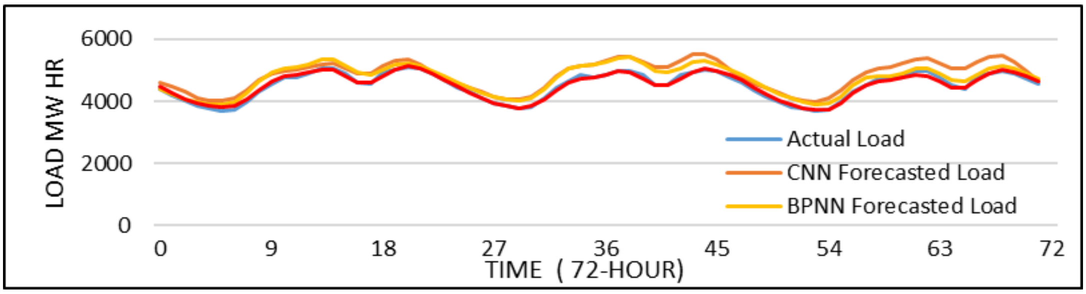


Fig. 6: A 72-hour sample load forecast of (a) CNN, (b) BPNN, and (c) parallel CNN-BPNN, and (d) a comparative plot of the three sample load forecasts.

The lowest, highest, and calculated average MAPE for each model is presented in Table 2, which derives from Figure 7. The parallel CNN-BPNN yielded a MAPE of 3.52%, BPNN 3.98%, and CNN 4.62%. Overall, the proposed model outperformed the other two models in speed and accuracy.

Table 2: Test accuracy of MAPE

Model	Low	High	Average
CNN	4.62%	8.70%	5.57%
BPNN	3.98%	8.43%	5.21%
Parallel CNN-BPNN	3.52%	4.13%	3.99%

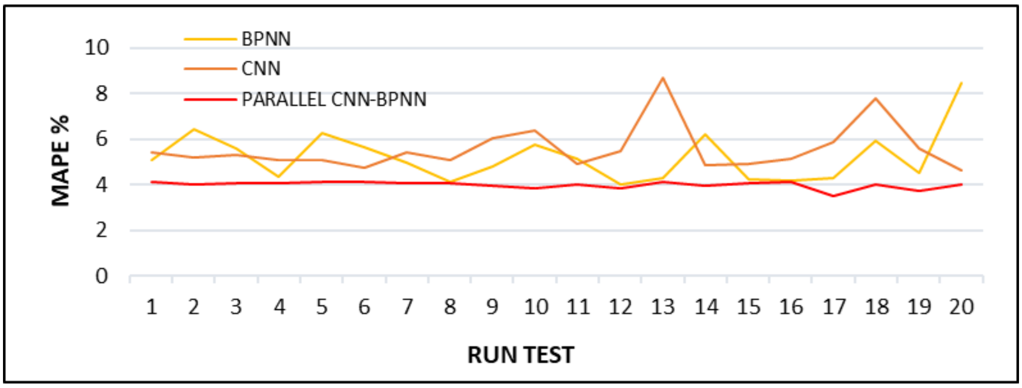


Fig.7: Test accuracy for CNN, BPNN, and parallel CNN-BPNN

5. Conclusion

Results showed that this study successfully applied a parallel CNN-BPNN algorithm in short-term load forecasting with COVID -19 pandemic restriction as an added input parameter and ReLU activation function. The successes of the study are detailed as follows.

The data treatment successfully converted the categorical data into a digital code using the one-hot coding. The strength of the relation between COVID-19 pandemic restriction and load demand was moderate, with a correlation value of -0.57. A functional CNN, BPNN and parallel CNN-BPNN forecasting models were implemented using Python programming language. Its training process resulted in the lowest rate of convergence of 480 seconds for the proposed model and the highest of 3,873 seconds for the BPNN. The proposed model yielded a MAPE of 3.52%, BPNN 3.98%, and CNN 4.62% in the testing phase. Lastly, comparison revealed that the parallel CNN-BPNN outperformed the other two models by at least 0.46%.

6. Recommendation

Improving SLTF accuracy through various models and other influencing factors is a continuing study. There are still emerging algorithms coming into machine learning that are worth verifying. A study using localized power and meteorological data can be conducted to see the difference from that of using regional data. It is also recommended to extend the analysis by assessing the economic impact in the generation sector by using the proposed model.

7. Acknowledgments

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