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AI-Driven Prediction of Electricity Production and Consumption in Micro-Hydropower Plant

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Micro hydropower plants must effectively manage demand response to preserve operational firmness and prevent system breakdowns. This research focuses on accomplishing a fine balance while predicting consumption and production, which is significant for upholding system integrity. The study delves into predictive modeling methods to forecast patterns in the production and consumption of electricity over an array of time horizons. We adopted a custom sliding window mechanism, in which actual and predicted values are used to predict the next hour of electricity. We set a baseline to resolve this and examined various algorithms, focusing on RNN-LSTM and CGP-LSTM. The CGP-LSTM forecasting output sequences with different time horizons precisely outperform the RNN-LSTM. The dataset utilized is downloaded from the Kaggle website. 50% of the data is used to train the models, and the rest is used to test the models. This work deals with the complex fluctuations in the demand response system and provides electricity production and consumption predictions. CGP-LSTM model gave a training MAPE of 6.67 (Accuracy of 93.33%) and a testing MAPE of 6.68 (accuracy of 93.32%) for the next three hours; on the other hand, LSTM gave a training MAPE of 6.53 (accuracy of 93.47%) and testing MAPE of 7.46 (accuracy of 92.54%) for the next three hours. The results offer a base for further developments and improvements in the field, drawing attention to more effective and reliable energy management capabilities in micro hydropower plants.

Keywords: Artificial Intelligence; Micro-Hydropower Plant; Time Series Forecasting; LSTM; CGP; Hourly Electricity Prediction

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Author's Contribution

I (Osman Safi) am the sole writer of this article, I played a key role in each part of the research, from formulation to completion. I have collected the data, developed the models, conducted experiments, and drafted the entire manuscript. while I obtained useful guidance and methodological guidance from my supervisor, Dr Gul Muhammad Khan. He brought novelty to this research by introducing the custom sliding window approach which is adopted in this research. My assistant supervisor Ms Gul Rukh Khattak has also provided feedback on my work, her input greatly refined my work.

Conflict of Interest

The authors declare that there are no conflicts in the publication of this article in IJIST.

Introduction:

The power production capacity of micro-hydropower stations is significantly affected by seasonal changes in water inflow, leading to electricity shortages and inconstant electricity supply. The Jungle-Inn Micro-Hydro Power Plant located at Swat, Kalam region is an example of such a case, where lower water intake during the winter time results in lower power output and persistent power production issues. To tackle this problem, the present load management exercises at Jungle-Inn MHP involve the temporary disconnection of one of the three-phase connections in case of decreased water inflow. And in case of excessive production, they switch on the water heaters to manage extra energy. However, these local practices prove neither safe nor optimal for stable and efficient power distribution systems. Voltage unevenness can result from a failure to forecast consumption changes or excess production, which could cause harm to the electrical infrastructure. The Jungle-Inn micro hydropower station case shows the issues encountered with handling surplus energy, where traditional approaches such as switching on heaters or sometimes diversion of water flow are insufficient. Precise prediction of production and consumption will allow more reliable and efficient load management practices.

Precise electrical consumption forecasting models are requirements because of certain driving motives, the most obvious and serious being climate change. With information being published, carbon dioxide emissions are one of the prime reasons for climate change [1]. The significance of electrical power in everyday life means that forecasting its consumption is increasing in importance. Because of their universal application, a range of articles, study papers, blogs, and videos are accessible. Referring to Weron's [2] prediction techniques, he examines several methods to handle the electrical energy forecast issue, including reduced form, statistical, and artificial intelligence, ML methodologies. It has been observed that Machine learning models frequently surpass many traditional approaches. It can still be split into different computational methods (ML models); one uses deep learning models based on neural networks to explore time-variant data, and the other contains time series models focused on regression techniques [3]. The auto-regressive moving average is one of the regression techniques (ARMA) [4], and the moving average model that is integrated auto-regressive (ARIMA) [5] such models needs to have highly reliable data [3] which might not always be attainable.

Electric company's planning operations rely on accurate models for forecasting electric power consumption. An electric company may use consumption forecasting to assist in making important choices about the production and consumption of electricity, load switching, and industry development. Accurately forecasting consumption requirements is an electric power utility's main task. Energy is considered fundamental to the modern world and a core aspect of economic sustainability. A renewable energy resource supply is essential for economic growth. Most renewable energy sources, including wind, solar radiation, geothermal heat, hydropower, etc., are long-term sustainable. For instance, the hydroelectric turbine systems of large-scale traditional hydroelectric stations, or dams, with water reservoirs offer varying electricity production in response to variations in energy consumption. Atmospheric factors like precipitation and temperature influence small and micro hydropower plants' ability to generate energy. Due to the previously mentioned, the energy produced by these systems varies and must be predicted [6]. Lately, the usefulness of artificial intelligence techniques has overtaken that of traditional approaches, in particular in the domain of electricity consumption forecasting. Notably, ANNs have acquired significant prevalence and have been extensively used in this field [7][8].

As reported by Weron [2], Several prediction methodologies, including reduced-form, statistical, and computational intelligence methods like Machine Learning (ML), have been explored to address the electrical power forecasting challenges. ML models have performed better than conventional approaches in different circumstances. This finding is by the results drawn by Pallabi Paik et al.'s research [9], Which concentrates on stock price prediction;

nevertheless, the research context is separate, and the resemblances between the data trend, data types, and setup in stock price prediction and electricity energy prediction suggest similar methods. Both domains concentrate on time series as the key element. The survey by Pallabi Paik et al. reveals that data-capturing technologies oftentimes outperform traditional techniques in multiple cases. These findings highlight the ability of machine learning approaches, including data mining, to offer more precise and firm predictions for complicated time series data like electricity energy consumption, outperforming the capabilities of conventional methods.

Deep learning models have shown better performance while operating on sequential data that show fickleness and volatility compared to traditional regression approaches. Notably, real-world data is frequently subject to dynamic alterations and instability. By means of experience-based data, research states the performance of artificial neural network models, namely the Long Short-Term Memory model, surpasses regression methods in such schemes. [3][10][11], These results highlight the importance of deploying deep learning approaches, such as LSTM, to achieve more precise and reliable forecasting when dealing with diverse and non-stationary time series data. The approach used in this study is implemented using a typical machine learning project workflow [12] as depicted below (Figure 1).

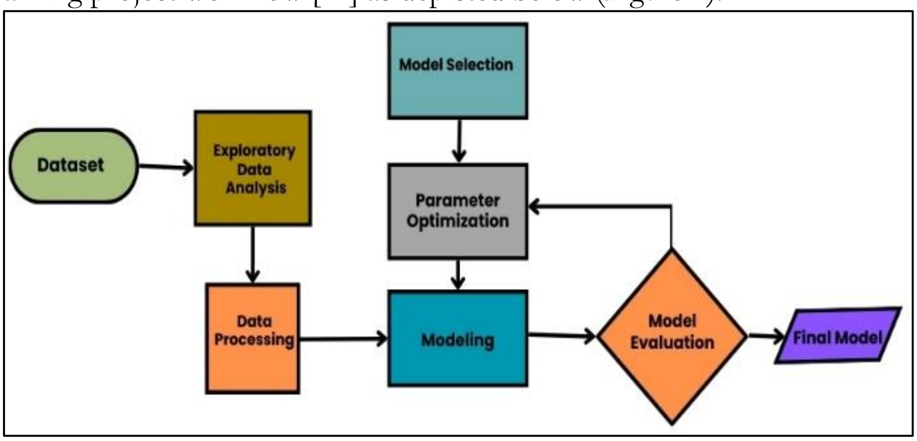

Figure 1: Research methodology adopted for this project [12]

The objectives of this research are to establish predictive models to precisely predict both electricity consumption and production for micro hydropower stations, enabling proactive management strategies to prevent unexpected alterations that could cause the system to fail. To continue to improve the effectiveness of load management strategies, it is vital to focus on the necessity of accurate predictions in light of rising electricity consumption and shifting dynamics in the environment surrounding the production of electricity.

Dummy Train Data	6352	6116	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	5776
	Train Data													
	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	Prediction	Actual
Core Model	6352	6116	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	Y1	X13
Update core model	6116	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	Y1	Y2	X14
Update core model	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	Y1	Y2	Y3	X15
Update core model	6116	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	Y4	X14
Update core model	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	Y4	Y5	X15
Update core model	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	Y4	Y5	Y6	X16
Update core model	5873	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	5776	Y7	X15
Update core model	5682	5557	5525	5513	5524	5510	5617	5643	5743	5737	5776	Y7	Y8	X16
Update core model	5557	5525	5513	5524	5510	5617	5643	5743	5737	5776	Y7	Y8	Y9	X17

Figure 2: Sliding window mechanism used in this project

We used a novel algorithm CGP-LSTM and adopted a custom sliding window mechanism, our approach entails leveraging the preceding 12 hours of electricity consumption to predict the subsequent 3 hours. We used actual and predicted values in the input sequence. This iterative process involves predicting one hour at a time, with each predicted value being appended to the input sequence for the subsequent prediction. Subsequently, upon completing a prediction cycle, the window of observed values is shifted by unit size, and the process is reiterated until the model is sufficiently trained.

Material and Methods:

The study's methodology follows a stepwise approach, using artificial intelligence algorithms to forecast the consumption and production of micro hydropower plants. The initial phase of research included finding a dataset that has the hourly-based consumption and production of electricity historical data. First, I went to Dare Noor an MHP located in Nangarhar province, Afghanistan the data that I acquired for Dare Noor was insufficient to conduct a successful training. The data for Jungle-Inn was not available at first so I looked it up on the Internet Finally, I downloaded a dataset named "Hourly Electricity Consumption and Production" [13] from the Kaggle website. The dataset has hourly time series of electricity consumption and production data in Romania spanning over four years. All values are in Mega Watts.

After finding the dataset, the next phase involved data pattern inspection and evaluation. By assessing these patterns, we can discover crucial insights about power consumption and production in different conditions. This analytical process enabled us to identify anomalies, trends, and potential fields of improvement. With the understanding obtained from the analysis of the data, we moved on to the development phase. Here, we have utilized different algorithms DNN, CNN, RNN, RNN-LSTM, and CGP-LSTM designed for optimal predictions. The algorithms are destined to forecast the consumption and production of electricity on the basis of historical data. The established models such as DNN, CNN, and RNN are trained, validated, and tested. The dataset is divided into three parts, which are 70% of the data selected for training, 20% of the data chosen for validation, and 10% of the data selected for the testing of the models. The training phase uses the data to train the model on different scenarios and predictable responses. After the model is trained, then it is validated against a separate set of samples from the dataset to ensure its generalization.

We additionally explore autoregressive methods utilizing RNN-LSTM and CGP-LSTM. The models are trained and tested using 50-50 data from the dataset. For the execution of the autoregressive approach, the model input includes both observed and predicted values, to predict the second and third-hours' electricity. However, to predict the first hour the models only used observed values from the dataset achieved by a custom sliding window approach. Eventually, this approach is favored to provide a permanent solution to the issues of load management during times of low water intake and excessive energy production thus enhancing the reliability and efficiency of the micro hydropower station.

Result and Discussion:

The primary goal is to predict power production and consumption for the next three hours. To achieve this a sliding window approach is used, where we use observed and predicted values as an input for prediction. This approach is practical for real-world applications, especially micro-hydro power stations. The dataset that was utilized for this project spans four years, from 2019 to 2023, and has three columns: "Date Time," "Consumption," and "Production" in MWh. We use different types of models for this task. Initially, we start with simple models to establish a baseline. Then, we explore more models, including Convolutional, DNN, and Recurrent Neural Networks. These models make all their predictions in a single shot (all 24 hours prediction at a single shot), unlike a sliding window approach where we predict one hour at a time and then we make the predicted hour part of an input, the input then have observed and predicted values to predict the next hour. In the final phase, we introduce an approach using a custom sliding window technique with LSTM and the novel algorithm called CGP-LSTM. We use the MAE and MAPE to assess the effectiveness of both forecasting models.

baseline model, linear model, dense model, CNN model, and RNN models.

RNN-LSTM:

In the experiments to train the LSTM model, we have used standardization as a normalization technique, we used 50% of the data to train the model and 50% to test the model on it. We used 12 nodes with the ReLU activation function. Here's a summary of the steps in the provided code:

- Import necessary libraries including NumPy, Pandas, and TensorFlow for building and training a neural network model.
- Define a function split-sequence (sequence, n_steps) to split a univariate time series sequence into input-output pairs with a specified number of time steps (n_steps).
- Set the number of time steps (n_steps) for sequence splitting and define a neural network model (core model) using Tensor Flow's Kera's API.
- Compile the core model with the Adam optimizer and mean squared error loss.
- Define column names for the result Data Frames for both training and testing.
- Create empty Data Frames Result Train and Result Test to store the training and testing results, respectively.
- Define a function Model Train (sequence, model) to train the neural network model on a given sequence. This function fits the model to the data, makes predictions, and appends the predicted value to the sequence.
- Define a function seq_train (raw) to perform training iteratively. It calls Model Train for training the model on subsequences of the training data, appends the results to Result Train, and updates the input sequence for the next iteration.
- Set the number of iterations and the raw data length initial values based on the length.
- Iterate through the training data, extracting subsequences and applying the seq_train function.
- Extract test data from the remaining portion of the raw data.

Figures 3 and 4 display the model's training and testing curves for 7000 data points.

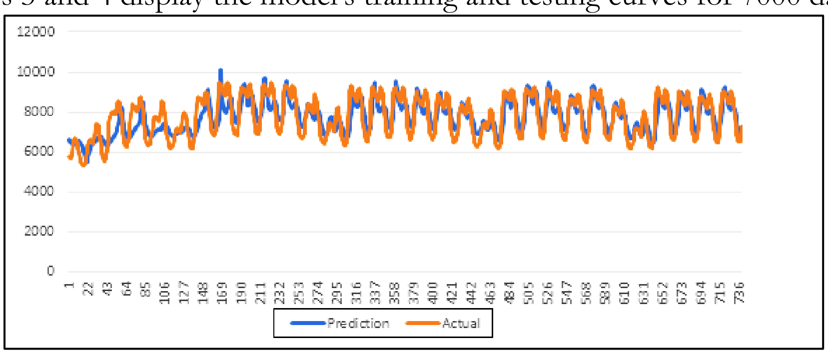

Figure 3: The training result of the model for 7k rows

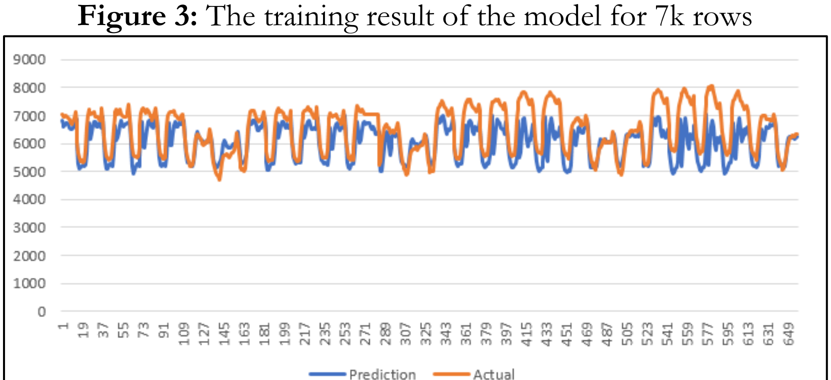

Figure 4: The testing result of the model for 7k rows

The following Figures 5 and 6 show the model performance when trained on 4k data samples.

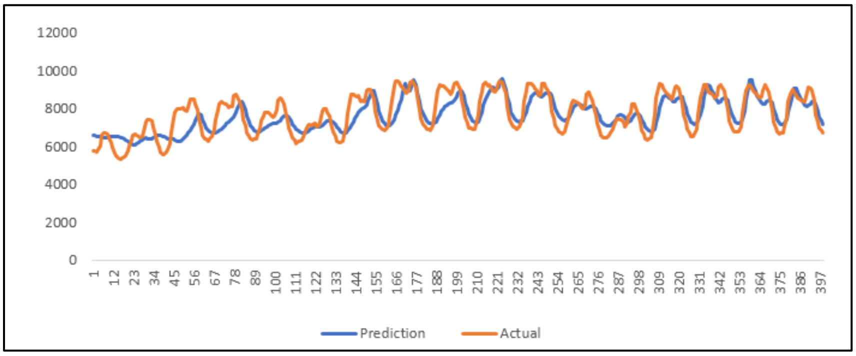

Figure 5: The training curves for 4000 rows

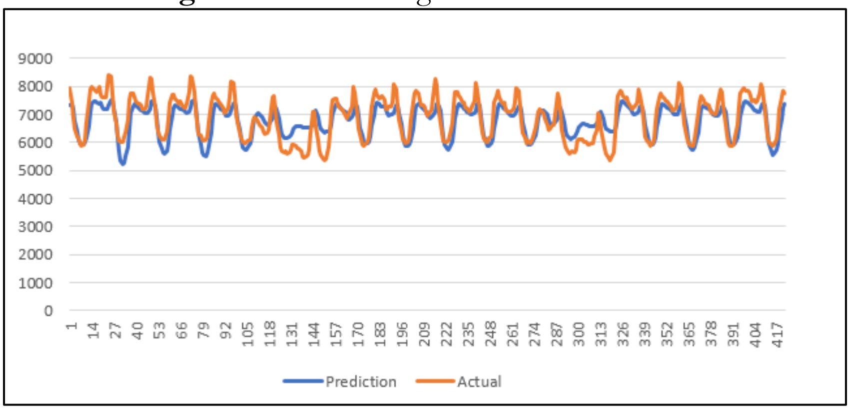

Figure 6: Testing curves for 4k rows

Table 1: RNN-LSTM model results

Model	Training/Testing	Input/output	MAE	MAPE
4k rows	Train C	12 inputs 1 output	363.47	4.86
	Test C		324.41	5.04
	Test P		340.91	5.21
	Train C	12 inputs 3 outputs	489.87	**6.53**
	Test C		450.11	**7.46**
	Test P		445.65	6.75
7k rows	Train C	12 inputs 1 output	279.813	3.92
	Test C		465.18	7.01
	Test P		392.77	6.69
	Train C	12 inputs 3 outputs	382.16	5.36
	Test C		678,81	10.2
	Test P		586.93	9.95

Table 1 presents a performance comparison of both of the experiments. The models are trained and tested on 4k and 7k data samples, providing one- and three-hour predictions into the future. The errors are presented in Megawatt hours (MWh). The model is trained and tested on both “Consumption” and “Production,” as you can see in the above table 1. The model is run on 4k and 7k rows from the dataset. “Train C” represents that the model is trained on “Consumption” historical data, “Test C” indicates that the model is tested on “Consumption” data, and “Test P” represents that the model is tested on “Production” data. In the experiment with 4k data points, we obtained an accuracy of **93.47 %** for training and **92.54%** for testing to predict the next three hours. The best results in the table are shown in bold text.

CGP-LSTM:

The CGP-LSTM training was carried out on the production data, and validation was performed on both the training and testing data. Figure 7 shows the actual and predicted values; the predicted values curve follows the actual values curve very closely.

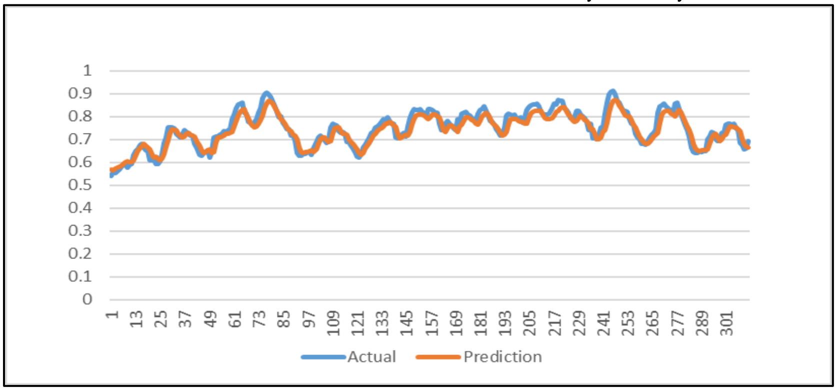

Figure 7: Testing result curve with CGP-LSTM algorithm

Table 2: Results of the CGP-LSTM model

Model	Training/ Testing	Input /Output	MAE	MAPE
50 Nodes Full datasets	Train- P	6 input 6 Output	0.064384	9.407604
	Test- P		0.062959	9.409408
	Test- C		0.048834	7.790334
	Train- P	6 input 3 output	0.045892	6.679367
	Test- P		0.044945	6.684573
	Test- C		0.035013	5.558505
	Train- P	6 input 1 one output	0.031806	4.589071
	Test- P		0.031083	4.583583
	Test- C		0.024525	3.869808

CGPLSTM used 50 nodes, although the actual nodes used in the model are fewer. The model is trained on the "Production" column from the dataset then it is tested on both "Production" and "Consumption", Train- P (Model trained on "Production"), Test-P (Model test on "Production), and Test –C (Model test on "Consumption"). As you see in Table 2, we have six inputs and 6 outputs, which means that based on the previous six hours, we are predicting the next 6 hours. Then we have three inputs and three outputs, which means that the model predicts the next three hours based on the previous six hours which have both observed and predicted values as explained in the custom sliding window approach. Finally, we have six inputs and one output, which means that we are predicting the next hour based on the previous six hours. When the model was first trained and tested on the entire dataset, the outcomes are displayed in Table 2.

Conclusion:

In conclusion, the various approaches and algorithms employed in this study present unique advantages and drawbacks, contributing to a detailed understanding of their applicability. Convolutional Neural Networks and Recurrent Neural Networks in the prediction process offer a robust foundation for capturing spatial and temporal dependencies in the data. CNNs stand out in extracting spatial features, whereas RNNs are adept at modeling temporal patterns. However, the dependency on vast training data and the possibility of overfitting are noteworthy drawbacks. Moreover, the autoregressive nature of the models presents challenges in precisely predicting distant subsequent values. Finding a balance between model complexity and forecasting accuracy is a key concern across all approaches. These insights help the continued discussion about the optimization of predictive modeling for electricity consumption and production prediction, leading the way for future improvements and refinements in the field. On the other hand, with its iterative prediction methodology using RNN-LSTM and CGP-LSTM, the Custom Sliding Window approach excels in its adaptability in yielding an output of varying lengths. This adaptability verifies advantageous in scenarios demanding several output predictions. However, the recurrent nature of the approach may present higher computational complexity. Comparing the results of these two established models, CGP-LSTM gave good results compared to RNN-LSTM. However, it must be mentioned that both models can be improved by experimenting with different combinations of hyperparameters. CGP-LSTM gave a training MAPE of **6.67** and a testing MAPE of **6.68** for the next three hours; on the other hand, RNN-LSTM gave a training MAPE of **6.53** and a testing MAPE of **7.46** for the next three hours. We have validated the RNN-LSTM model on the Jungle-Inn dataset, which contains hourly data spanning 65 days. The results are promising, and in the future, when more data is available, the same method can be extended.

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