Deep Learning Technique in Geothermal Energy Detection

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Abstract**—** to meet the current demand for energy consumption by commercial industries and families, utility companies are heavily investing in the production of renewable energy. Renewable energy is obtained from natural resources on the planet. Solar, biogas, geothermal, hydroelectric, wind, solar thermal, and other renewable energy sources are the most popular. Conventional energy sources have a negative impact on the environment and the economy; so, a mix of energy sources with a majority percentage of sustainable energy sources is urgently needed. Renewable energy is a viable alternative to traditional energy, and it has a lower environmental impact. To estimate the amount of energy produced in a given year, forecasting energy generation from sustainable sources is essential. Energy generation from sustainable sources must be predicted in order to estimate the amount of energy produced in the future to fulfill rising energy consumption demands. In this research, we show how to use an LSTM (Long Short Term Memory) Sequence to Sequence Encoder-Decoder Neural Network architecture to estimate geothermal energy production.

Keywords**—**Renewable Energy, Geothermal, Prediction, Deep Learning, Recurrent neural networks, Long Short-Term Memory.

I. Introduction

With the rise in energy use by commercial industries, businesses, and homes, our planet has faced numerous challenges. Utility firms have constructed massive power plants to generate energy from traditional sources. This has a significant impact on environmental protection and human welfare. The globe has been driven to develop alternate and constructive power sources due to the exhaustion of non-renewable energy reserves and the environmental impact of burning these fuels. In the power industry, sustainable energy sources such as geothermal, hydropower, wind power, tidal waves, and biomass have been rapidly developing [1] and [2].
Presently, the expenditure of conventional energy sources is drastically increasing along with the population of the world. It has long been recognized that excessive usage of traditional energy supplies is not only depleting limited fossil fuel reserves, but also producing adverse environmental repercussions such as global warming and a variety of health-related issues.

As a result, humanity is moving toward alternative energy sources, generally known as renewable energy sources. Nature is always renewing or replenishing these renewable energy sources. The production and demand for these energy sources are both on the rise. This will be good for the environment because burning conventional energy sources pollutes the air, and it will benefit public health.

Due to the aforementioned challenges, we decided to develop a predictive analytical model based on a deep learning algorithm. This study will describe historical data-based predictions for geothermal energy output in the future.

II. Related Work

Inference from data is frequently obtained using learning-based algorithms [3, 4]. Several publications utilizing a form of Recurrent Neural Network termed LSTM for prediction on time-series data have been published [5].

A work on solar irradiance prediction was released by Xiangyun Qing and Yugang Niu (2018) [6]. They used data from a solar energy station for 30 months to compile their report. They compared the outcomes of several methods for irradiance prediction, including linear least square regression, persistence algorithm, multilayered feed forward neural networks employing back propagation algorithm (BPNN), and LSTM. They discovered that LSTM was 18.34 percent more accurate than BPNN in terms of root mean square error (RMSE) and had greater generalization capacity than BPNN.André Gensler et al. (2016) [7] published a paper on solar power forecasting. In this paper, they collected the solar

Power data in kW from 21 photovoltaic facilities in Germany. They employed five algorithms to forecast solar energy output: Multilayer perception (MLP), LSTM, Auto Encoder, and Auto-LSTM, which is a combination of Auto Encoder, LSTM, and Deep Belief Network (DBN). They came to the conclusion that the Auto-LSTM model performed the best and had the lowest RMSE value. A work on building energy prediction was released by Idil Sülo et al. (2019) [8]. They employed the LSTM model to examine and estimate the power expenditure of real estate housings at City University of New York in this paper (CUNY). They also looked into several ways to improve the energy efficiency of these structures. Temperature and humidity together provided the best accuracy among the numerous characteristics for energy prediction, they discovered. In this paper, we propose a similar approach using a LSTM Encoder-Decoder Model to predict the geothermal energy.

III. RNN-LSTM (Long Short-Term Memory)

The (LSTM) model is a variation of RNN that successfully solves the problem of vanishing gradient in traditional RNNs. LSTM comprises of cell memory which reserves the encapsulation of past input series, along with the gated system through which the movement of data among the cell memory, input and output are managed [9].

The subsequent equations explain the working of LSTM:

$$f_t = \sigma\,(W_{uf}u_t + W_{hf}h_{t-1} + g_f) \tag{1}$$

$$k_t = \sigma\,(W_{ui}u_t + W_{hi}h_{t-1} + g_i) \tag{2}$$

$$m_t = \sigma\,(W_{uo}u_t + W_{ho}h_{t-1} + g_o) \tag{3}$$

$$v_t = f_t * c_{t-1} + i_t * \tanh(W_{uc}u_t + W_{hc}h_{t-1} + g_c) \tag{4}$$

$$j_t = m_t * \tanh(v_t), \tag{5}$$

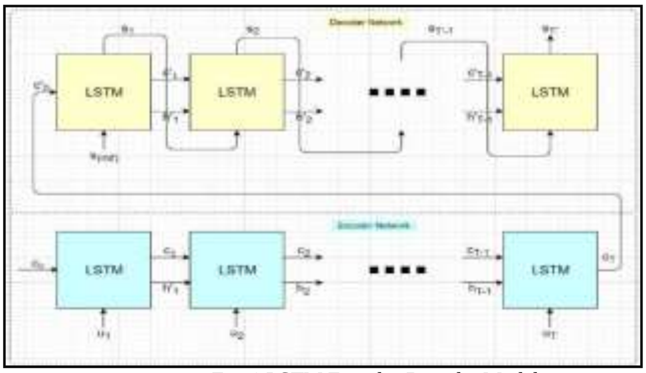

Fig. 1 LSTM Encoder-Decoder Model

where,

- $\sigma\,(x) \triangleq \frac{1}{1+\exp(-x)}$: sigmoid function
- u_t: input vector
- W_{ui}, W_{hi}, W_{uf}, W_{hf}, W_{uo}, W_{ho}, W_{uc}, W_{hc}: linear transformation matrices
- g_i, g_f, g_o, g_c: bias vectors
- k_t, f_t, m_t: gating vectors
- c_t: cell memory state vector
- h_t: state output vector

IV. LSTM Encoder Decoder Model

The LSTM Encoder-Decoder model was initially introduced for problems such as machine translation [10], [11], and [12]. It has the capability to peruse and produce a series of random series as shown in Fig. 1. The model utilizes two LSTM architectures known as the decoder and encoder. The encoder acts on the input series $u_1, \ldots, u_T$ of length T and produces an encapsulation of the old input series by the cell state vector c_t. After T times of recurrent adjustments from (I) to (V), the encoder encapsulates the entire input series into the final cell state vector c_T. After that, the encoder transfers c_T to the decoder and then the decoder utilizes it as an inceptive cell state ($c' = c_T$) for the series production. The decoding part is commenced with a mock input $s_{(init)}$ [13]. The decoder recurrently produces the output series $s_1, \ldots, s_{T'}$ of length T´. After each adjustment, the decoder passes the output s_{t-1} acquired in the preceding adjustment to the input for the present adjustment. The output of the decoder is attained by putting in the affine transformation subsequently the activation function which is suitable for the problems.

Essentially, the LSTM encoder-decoder targets to model the conditional probability of the output series when the input series is given, i.e., $p(s_1, \ldots, s_{T'} | u_1, \ldots, u_T)$. The encoder presents the encapsulation of the input series $u_1, \ldots, u_T$ by the LSTM cell state c_T [14]. The conditional probability when the encoder cell state c_T is given is calculated as-

$$p(s_1, \ldots, s_{T'}|u_1, \ldots, u_T) \approx \prod_{t=1}^{T'} p(s_t|c_T, s_1, \ldots, s_{t-1}) \tag{6}$$

The decoder consecutively generates the probability distribution of $p(s_t|c'_{t-1}, s_{t-1})$ given the decoder cell state c'_{t-1} and the $(t-1)$th sample of the output series s_{t-1}, which is given by-

$$p(s_1, \ldots, s_{T'}|u_1, \ldots, u_T) \approx \prod_{t=1}^{T'} p(s_t|c'_{t-1}, s_{t-1}) \tag{7}$$

The decoder, unfortunately, lacks the actual value of the previous output sample. Therefore, in each decoding step, the decoder based on the probability distribution $p(s_t| c'_{t-1}, s_{t-1})$, makes a decision on s_t attained from the decoder output and utilizes the provisional conclusion for the subsequent adjustment of the decoder state [15].

V. Proposed Approach

The dataset contains univariate time-series data and the production of different renewable energies such as Geothermal, Biomass, Biogas, Small Hydro, Wind, Solar PV, and Solar Thermal measured in MW. The data was recorded every hour from the year 2010 to 2018. We focused on the production of Geothermal energy data, sliced it and used only 2017 data to predict the geothermal energy for 2018 and obtained the test accuracy.

We trained our LSTM Sequence-to-Sequence encoder-decoder model using this dataset with optimal hyperparameter optimization as shown in Fig. 2.

The link for the dataset is given below-
https://www.kaggle.com/cheedcheed/california-renewable-production-20102018

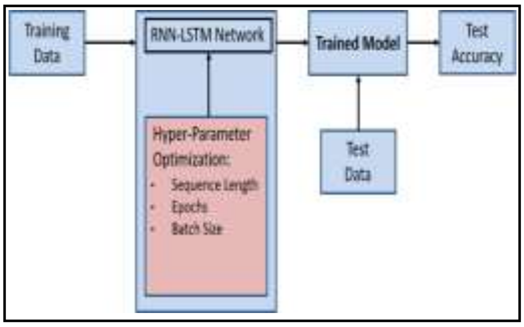

Fig. 2 Process Flow

VI. Result Analysis

A. *HYPERPARAMETER SELECTION AND OPTIMIZATION*

1) *BATCH SIZE*

The batch size is a terminology utilized in Deep Learning and relates to the number of training samples used in a single iteration. We used three batch sizes i.e. 32, 128 and 512 to optimize the accuracy. Among them, the best accuracy was achieved when the batch size was 128 as shown in Fig. 3.

Fig. 3 Batch Size vs Accuracy

2) *EPOCHS*

Epoch is a term that refers to the number of times the training algorithm will work through the entire training dataset. One epoch means that each example in the training dataset has had a chance to update the internal model parameters. An epoch contains one or more batches. We used a wide range of epochs to optimize accuracy. The best accuracy was achieved when the number of epochs was 100. Accuracy and Loss value w.r.t epoch are shown in Fig. 4 and Fig. 5 respectively.

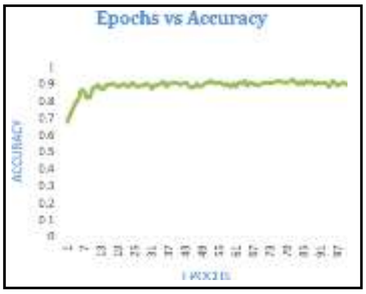

Fig. 4 Epochs vs Accuracy

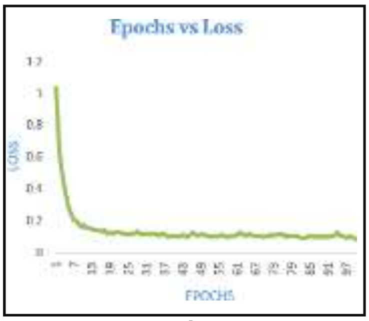

Fig. 5 Epochs vs Loss

3) *SEQUENCE LENGTH*

A sequence is a vector of a fixed length. The encoder in the LSTM Encoder-Decoder model reads an input sequence and encodes it into a fixed-length vector. The decoder decodes this fixed-length vector or sequence and outputs the predicted sequence. We trained model with 4 different sequence lengths i.e. 3, 5, 10, and 15 to optimize the accuracy. Among the four sequence lengths, the best accuracy was attained when the sequence length was 10.

The results with different sequence lengths are shown in Fig. 6:

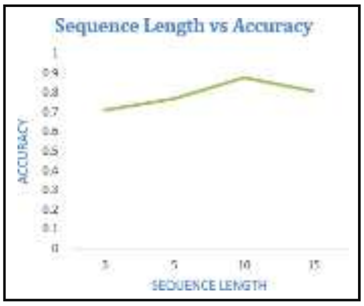

Fig. 6 Sequence Length vs Accuracy

$$\text{Accuracy} = \frac{\text{Total number of correct predictions}}{\text{Total number of input samples}}$$

The different hyperparameters, their final optimized values and the best accuracy achieved are summarized in Table 1.

TABLE 1. Summary of Optimal Values and Accuracy

S.R NO.	HYPERPARAMETER	OPTIMAL VALUE	ACCURACY
1	Batch Size	128	0.92
2	Epochs	100	
3	Sequence Length	10	

VII. Conclusion and Future Work

We used an LSTM Encoder-Decoder model to estimate geothermal energy generation in this paper. The proposed method uses an LSTM encoder to learn previous geothermal energy production and an LSTM decoder to predict future geothermal energy production based on the encoder output. To achieve the best accuracy, we tweaked batch size, epoch, and sequence length. Our LSTM model properly predicted future geothermal energy production needs with 92 percent accuracy. In the future, we want to use alternative neural network designs to estimate the generation of other renewable energies for the best results.

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