

Iot Based Solar Power Monitoring And Prediction Using Cuckoo Optimized LSTM

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Abstract

In today's world, the sun is the easiest and commercially feasible way of renewable energy. The modern electrical grid poses new difficulties due to its intermittent and variable nature. Soft computing-based energy monitoring and prediction techniques are used to handle these difficulties. In this work, IOT based solar power monitoring system is proposed with deep learning-based prediction. The proposed embedded system includes Arduino based controller ESP module to collect data in the server. Long short-term memory (LSTM)-based deep learning method for predicting energy generation of a solar. In order to achieve higher accuracy, cuckoo search-based optimization is applied to optimize LSTM parameters. The proposed e setup compared with other methods.

Introduction

Internet of Things (IOT) is an innovative technology that allows hardware devices can be controlled or monitored through the cloud server. Nowadays, it is used in smart grid, home automation, and machine to machine communication, etc.

Solar-based energy is a most encouraging renewable source for generating power for residential, commercial, and industrial applications. Power generation based on solar systems has added much attention from scientists and specialists recently due to its needed characteristics.

Accurate predicting of the power output of solar systems in the short term is of excessive significance for daily/hourly proficient controlling of power grid production and also for decision-making on the energy market.

Deep learning is a supervised learning method for accurate predictions of a huge amount of data. Energy prediction is an important task in power sectors for saving energy and for economical benefits. So, there is a need demand for forecasting algorithms for accurate prediction. With the progress of power reform and the excavating of

power marketization, energy load predicting has become more perilous in the energy system.

Related work

Exact forecasting of solar power is essential for photovoltaic-based energy using industries to simplify early contribution in energy markets and for resource preparation. Many approaches have been proposed in the literature for power forecasting.

Chai et al. 2019 have introduced aAHPA-LSTM based model for solar energy prediction. In order to improve prediction accuracy, the momentum resistance method is used to update the weight of the LSTM circuit. The learning rate is high when compared to other methods.

Xu et al. 2018 have proposed a wind power forecasting system using an adaptive LSTM network. The Pearson correlation analysis is utilized for feature extraction. The overall prediction accuracy is high when compared to other machine learning algorithms. QuXiaoyun et al. 2016 have proposed a deep learning-based wind power prediction. Principal component analysis used for valuable extraction data from numerical weather prediction(NWP) and to reduce the dimensionality of data. Zhang et al. 2018 have proposed a combined prediction method for fault detection using LSTM and support vector machine (SVM). The temporal features are extracted using SVM. LSTM for data classification. The health parameters of the system are predicted using ELM for future references.

Krishnan et al. 2020 have proposed a hybrid model for energy prediction .the proposed model combines genetic algorithm with LSTM for accurate prediction. Genetic algorithm used for leading LSTM to train properly.

Proposed work

The proposed embedded system includes Arduino based controller ESP module to collect data in the server. Long short-term memory (LSTM)-based deep learning method for predicting energy generation of a solar. The proposed block diagram is shown in figure 1.



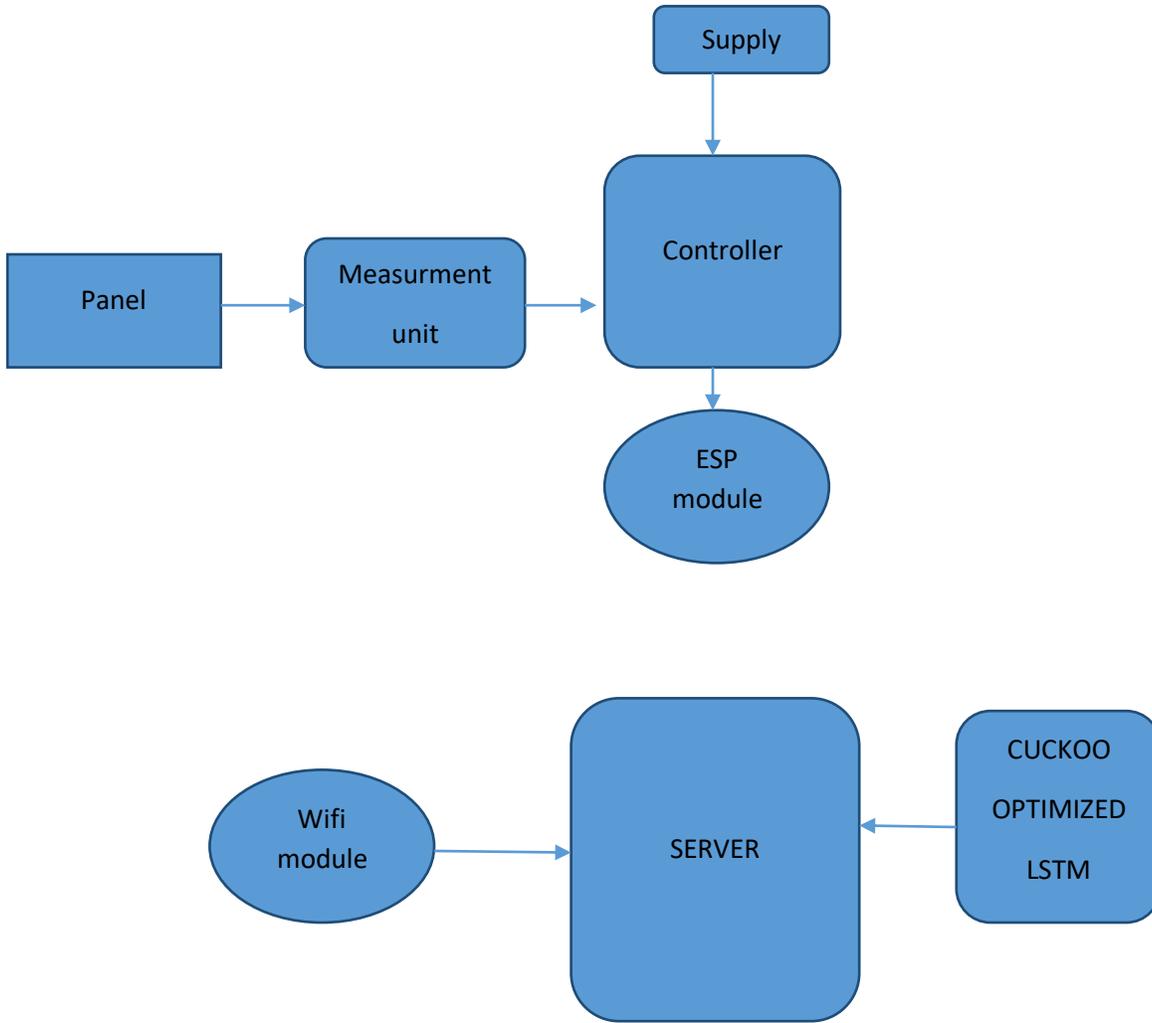


Figure 1 Proposed system

LSTM

LSTM is a type of recurrent neural network used for accurate prediction. It is used to overcome the drawback of recurrent networks and add extra functions for prediction like the input gate, the forget gate, and the output gate. The expression for computation as follows

$$\begin{aligned}
 A_t &= \tanh(W_{cur}X_t + R_{cur}H_{t-1}) \\
 I_t &= \sigma(W_{inp}X_t + R_{inp}H_{t-1}) \\
 F_t &= \sigma(W_{for}X_t + R_{for}H_{t-1}) \\
 O_t &= \sigma(W_{out}X_t + R_{out}H_{t-1}) \\
 C_t &= I_t \odot A_t + F_t \odot C_{t-1} \\
 H_t &= O_t \odot \tanh(C_t)
 \end{aligned}$$

Cuckoo Search algorithm

The Cuckoo Search algorithm is a meta-heuristic optimization algorithm used to solve engineering problems inspired by the brood parasitism of some cuckoo species, along with Levy flights random walks. The objective is to work the new and hypothetically better solutions (cuckoos) to substitute not-so-good solutions in the nests. When producing new solutions $x(t+1)$ for, say, a cuckoo is a Lévy flight achieved.

$$X_i^{(t+1)} = X_i^{(t)} + \alpha \oplus \text{Lévy}(\lambda)$$

Where $\alpha > 0$ is the step size which should be connected to the measures of the problem of interests & in most cases

In this work, a cuckoo search applied in LSTM to set optimum window size and tune a hyperparameter automatically to achieve higher accuracy.

Result and discussion

LSTM model formed by trained data. Arduino controller collects data from voltage and current sensor and sends it to cloud server. The proposed hardware setup is shown in figure 2. The proposed prediction model is

compared with the standard algorithm of Support Vector Machine-based Regression. The forecasting result indicates the efficiency of the proposed model in terms of accuracy and means square error (Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)). Table 1 shows the measured performance values of the proposed system.

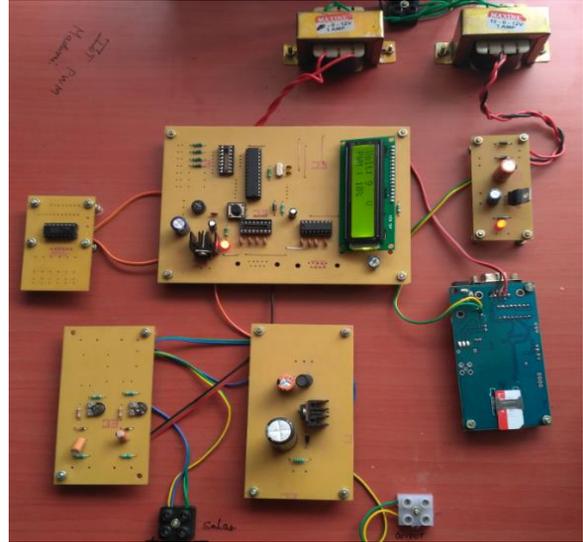


Figure 2. Hardware set up

Table 1 Performance analysis

Method	MSE	MAE	MAPE
SVR	195.6	14.5	0.9
LSTM	169	9	0.6
CS-LSTM	165	6.2	0.49

Conclusion

The main contribution of the proposed works is to propose IOT based solar power monitoring system with LSTM based prediction. The main difficulties in solar power production are the instability of intermittent solar system power production due primarily to climate circumstances. In this work, the LSTM model effectively predicts the data by supervised training. Results show hopeful power predicting results of LSTM.

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