A Case Study of Using Long Short-Term Memory (LSTM) Algorithm in Solar Photovoltaic Power Forecasting

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Solar photovoltaic power plays an important role in distributed energy resources. The number of solar-powered electricity generation has increased steadily in recent years all over the world. This happens because it produces clean energy, and solar photovoltaic technology is continuously developing. One of the challenges in solar photovoltaic is that power generation is highly dependent on the dynamic changes of environmental parameters and asset operating conditions. Solar power forecasting can be a possible solution to maximise the electricity generation capability of the solar photovoltaic system. This study implements the deep learning method, long short-term memory (LSTM) models for time series forecasting in solar photovoltaic power generation forecasting. The data set collected by The Ravina Project from 2010 to 2014 is used as the training data in the simulations. The root mean square value is used in this study to measure the forecasting error. The results show that the deep learning algorithm provides reliable forecasting results.

Keywords: renewable energy; solar power forecasting; deep learning algorithm; time series prediction

I. INTRODUCTION

The global trend of energy sources has shifted towards renewable energy in the last few decades. It has driven the development of solar photovoltaic technology. The production cost of electricity from solar photovoltaic dropped significantly while the energy conversion efficiency has increased. This makes solar photovoltaic energy an alternative energy source in many countries. However, the solar photovoltaic system poses a significant limitation, which is the uncertainty of power generation. It depends heavily on weather conditions such as solar irradiance, cloud cover, wind velocity, etc (Rana *et al.*, 2016). This affects the quality of the connected electrical system. Thus, solar power forecasting plays a vital role in solar photovoltaic plant installation, process, and reliability of solar power transfer. To accomplish a high penetration of commercial solar power

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into the grid, practical power forecasting approaches should be developed for the electric grid by integrating solar power. The current research on the electrical grid mainly focuses on the safety and reliability of distributing power from generation sources by advanced monitoring and control of transmission lines to the distribution lines. This encouraged the performance monitoring and control of the photovoltaic system processes.

Solar power generation reliability, stability, and planning strongly depend on the accuracy of power forecasting. It provides essential information to the electricity providers and independent system operators to reduce the uncertainty of solar power generation. To achieve the high accuracy of power forecast in solar power generation, information such as weather records, solar irradiance, and solar power generation monitoring data must be provided by the forecasting system (Fan *et al.*, 2021). The dynamic change of weather parameters and cloud cover are the critical factors of forecasting accuracy for the day-ahead forecast. Another issue that affects solar power forecasting accuracy is the irradiance values.

The mathematical approach has been used widely to forecast solar power generation. The techniques can be classified into two: persistence models and statistical methods. Unluckily, these techniques have low forecasting accuracy and do not work correctly when non-linear data is applied. To reduce the limitation, machine learning and metaheuristic techniques have been applied in forecasting. Machine learning can handle problems that are unsolvable by an explicit algorithm. It can develop a relationship between inputs and outputs without concerning their representation (Akhter et al., 2019). This makes it suitable to be used for forecasting. The machine learning techniques commonly used in solar power forecasting can be classified into three; numerical/statistical, physical, and hybrid. Machine learning, such as artificial neural networks, extreme learning machines, and support vector machines, are classified under statistical techniques. It extracts information from historical data to forecast time series. Meanwhile, physical techniques like numerical weather prediction, satellite/remote sensing, and sky model depend on the physical state and dynamic motion. The hybrid techniques involve a combination of both statistical and physical.

There is another subset of machine learning techniques called deep learning. It is the next evolution of machine learning. Deep learning algorithms are eventually inspired by the pattern of information processing found in the human brain. It works like our brain to classify different types of information and identify the pattern of the information. Deep learning uses the training loop to learn and accomplish the same tasks. It also deciphers the information received, just like the human brain, by transferring and classifying the items into various groups. Deep learning has shown the strengths of representation learning and time series in forecasting research lately. It delivers good results for real-time prediction, particularly for learning from the dynamic changes in environmental conditions. It provides better accuracy forecasting results. Thus, it motivates the researchers to study the deep learning algorithm, especially in solar power forecasting. This paper aims to investigate the performance of a deep learning algorithm, the LSTM when applied in solar power generation.

The paper is organised as follows: Section II reviews the literature containing solar power forecasting methods that use machine learning and deep learning. Section III discusses the methodology for this research. LSTM is adapted for solar photovoltaic power forecasting, and the simulations are performed using MATLAB. The data set from the Ravina Project is used for this study. Section IV presents the result and discussion. The conclusion is written in the final sections.

II. RELATED WORK

Solar power forecasting is not a new research topic. A good survey of solar power forecasting paper can be found in (Inman *et al.*, 2013). Ferrero Bermejo *et al.* (2019), Foley *et al.* (2012), Giebel *et al.* (2011), and Lei *et al.* (2009) wrote review papers that cover other types of renewable energy power forecasting. Various forecasting techniques have been introduced. They can be grouped into short-term techniques, which are covered by Costa *et al.* (2008), mid-term techniques by Mirasgedis *et al.* (2006), and long-term techniques by Hong *et al.* (2014).

Machine learning is a popular technique for forecasting tasks. It was integrated with other mathematical prediction models for solar power forecasting. For example, the numerical weather prediction (NWP) technique was used together with machine learning by Li et al. (2016) to forecast the cumulative sum of solar power generation for the places separated by the geographic cluster. The results showed an improvement in the accuracy of forecasting compared with the existing technique. The fuzzy inference method was used by Yang et al. (2014) to select an adequately trained model; meanwhile, machine learning techniques such as self-organising map, learning vector quantisation, and support vector regression (SVR) were used for data classification, learning, and training, respectively. These works presented better results than artificial neural networks and simple SVR techniques. The genetic algorithm was used for bulk and threshold optimised by Luo et al. (2017) to overcome an over-appropriate scene