MULTIVARIATE TIME SERIES ANALYSIS OF SOLAR IRRADIANCE FOR PHOTOVOLTAIC SYSTEMS: THE HYBRIDIZATION OF NARX AND LSTM MODELS

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INTRODUCTION

1.1 Research Background

Degradation of the environment is the most difficult challenge in nations that have been detribalized, and the argument that it is not a concern in countries that have not been industrialized is no longer relevant [Yoldaş et al., 2017]. The high emissions of greenhouse gases (GHGs) are having an effect on both industrialized and non-industrialized nations all over the world. The rise in energy consumption that is a direct result of the expansion of the human population is the root cause of environmental deterioration. In 2023, the CO2 emissions record had shown that the reading of CO2 had reached 37.4 Gt [Raimi et al., 2024] where is considered the highest record. Which led many countries to focusing on replacing the traditional power grid like Coal-fired power station where they use the concept of coal-combustion to generate electricity, to the renewable energy sources which is more sustain and safe on the environment.

For this reason, the development of clean and renewable energy sources has emerged as a crucial approach for the economic and social sustainability of development for every nation on the planet [Suman et al., 2021]. The idea of a microgrid was proposed by the researchers in order to resolve the conflict that exists between grid generation and distributed generation, as well as to make the most of the benefits that distributed generation offers in terms of the economics, energy, and the environment.

Microgrids, localized power systems that can operate independently or in conjunction with the traditional power grid structure as shown in Figure 1.1, represent a compact yet fully operational grid system, functioning within a confined geographical region [Raimi et al., 2024]. Typically, a Microgrid (MG) is characterized as a combined energy provision system composed of various Distributed Generations

(DGs), energy storage components, loads, and devices for monitoring and protection. It functions as an independent, self-sustaining system that interfaces with the broader grid as a unified, regulated entity [Sepasi et al., 2023]. This system is endowed with the ability for self-regulation, protective measures, and overall management, all while satisfying the customer's expectations for reliable power supply and high-quality electricity.

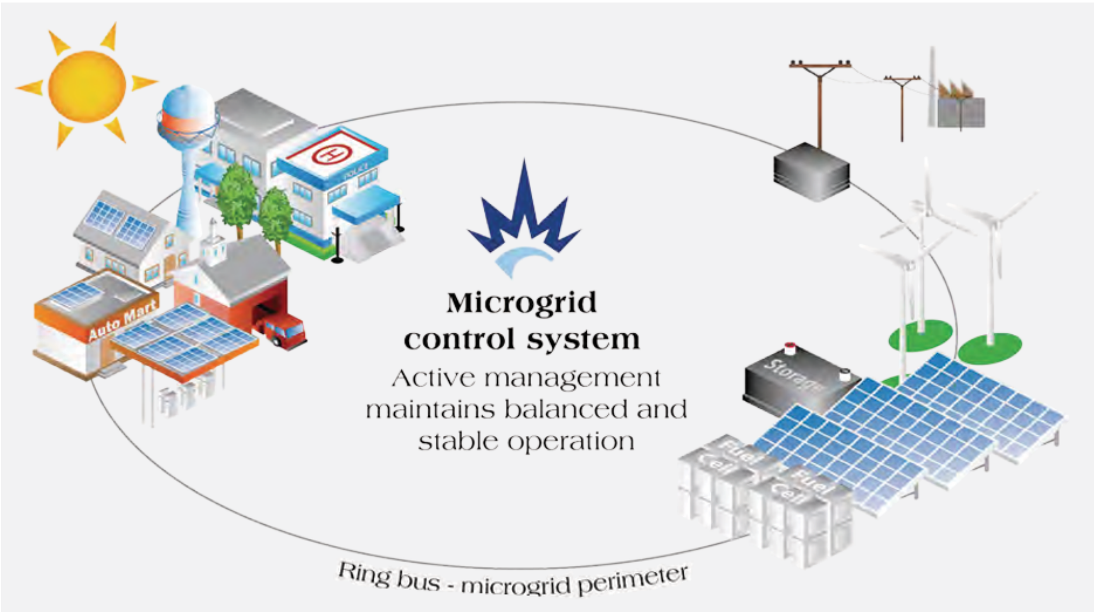

Figure 1.1 Architecture of an MG [Bank, 2020].

The shift to renewable energy is a worldwide movement in the twenty-first century. Solar energy is driving this change because of its huge resource potential. Photovoltaic (PV) energy offers significant availability and extended longevity to stakeholders. As well as there are many technologies that had been developed in field of solar energy in terms of improving the power efficiency (PV cell) also the development reach to the storge system where it can help in improving the isolated system and the hybrid system [Dutta et al., 2017]. However, photovoltaic energy exhibits several constraints about inadequate power stability and subpar power quality. Photovoltaic plants are consistently affected by meteorological factors like cloud cover, wind velocity, and temperature fluctuations. Moreover, the primary impetus for energy production, namely irradiation, is only accessible during daylight hours [Shakya et al., 2016].

Consequently, forecasting models have been extensively used for photovoltaic systems to predict produced photovoltaic power on one hand and load demand on the other, so facilitating intelligent demand response and efficient energy management.

For the purpose of forecasting the solar irradiance, researchers are employing a wide range of methodologies. These methods may be generally classified into four categories: data-driven approaches, image-based approaches, numerical weather prediction (NWP) models, and hybrid approaches [Guermoui et al., 2020]. For the purpose of forecasting the solar time series, data-driven or statistical and machine learning methodologies make use of the historical data that has been observed or felt in the past. Images obtained from sky/shadow cameras or satellites are utilised by image-based techniques, which then integrate this information with past data in order to eventually anticipate the irradiance. For the purpose of predicting the irradiance, NWP models make use of computer-based programs. There are a variety of hybrid or combination models, which are diverse combinations of two or more of the types that were originally listed. However many methods facing difficulty to accurately forecast the solar irradiance due to many factors.

Machine learning (ML) approaches have been suggested up until this point in order to comprehend the behavior of selected feature patterns that are constantly changing over time in order to reconstruct a clear vision about future values [Massaoudi et al., 2020]. In layman's terms, these methods examine the past (the data that was input) in order to make predictions about the future (the behavior of the system). Direct and indirect PVPF are the components that make up Photovoltaic power forecasting (PVPF). On the one hand, direct PVPF evaluates the meteorological data from the past in order to forecast the amount of electricity that may be generated by PV. The indirect PVPF, on the other hand, employs an approach that consists of two stages. When it comes to the initial stage, the solar irradiance is anticipated to be the PV power aspect that is most dependent on it. Within the second step, the determination of the power generated by photovoltaic cells is based on mathematical relationships [Massaoudi et al., 2019]. According to the findings presented in [Lei and Yang, 2019], it has been demonstrated that the second technique is superior in terms of accuracy, versatility, costability, and the amount of computing effort that it requires. According to the authors of [Akhter et al., 2019], hybrid models can obtain competitive outcomes in comparison to the approaches that are considered to be state-of-the-art by merging two or more single machine learning models from different sources.

According to the approaches of forecasting that are now in use, there are a few handles that continue to require additional mastery. To begin, the range of prediction for weather forecast data is restricted, and the historical time series of solar power is non-stationary, dynamic, and nonperiodic. These characteristics make it impossible for typical artificial intelligence systems to comprehend the data. In the second place, the input-output prediction patterns of the current modes are investigated from the point of view of statistical analysis. This approach either disregards the effect of other connected elements or necessitates the collection of high-quality data from many associated factors, which restricts the practical applicability. In conclusion, the complex non-linearity of the photovoltaic time series over different forecasting horizons exists between univariate time steps and among the variables that are significant.

To address the current challenges and achieve precise photovoltaic power forecasting, the hypothesis of the proposed method in this paper is primarily based on the following considerations where the current research indicates that NARX effectively manages nonlinear relationships, while LSTM excels in extracting temporal features, and the attention mechanism mitigates the issues of distraction. hence, the hybridization of NARX and LSTM is proposed in this study.

1.2 Problem Statement

The total capacity of renewable energy sources around the globe reached 3,381 gigawatts in the year 2023. With a capacity of 1053 gigawatts (GW), solar energy has emerged as the second most widely adopted of these renewable sources for energy production. Malaysia is positioned as top four nations in Southeast Asia in terms of its significant solar energy capacity. In the present moment, renewable energy sources provide 13.3% of Malaysia's overall energy capacity, it is anticipated that Malaysia would attain 18.2% of its capacity to generate electricity from renewable sources by 2025, and 70% by 2050. Consequently, the amount of integration of the renewable energy with the main grid will increase exponentially which will increase the complexity in terms of gird management, and stability within the gird due to the difficulty in renewable energy forecasting. Therefore, to achieve the integration with RE, an accurate and strong forecasting model is required for predicting the solar energy.

1.3 Research Goal

The aim of the project is to present a hybrid nonlinear autoregressive network with long-term memory inputs and exogenous inputs (NARXLSTM) model to meet the growing need for accurate daily solar irradiance predictions, especially under volatile weather conditions in Malaysia.

1.4 Research Objectives

(a) To develop a hybrid machine learning model combining LSTM and NARX neural networks, focusing on improving the precision of daily solar irradiance predictions.

(b) To analyze the influence of various weather parameters, determining their individual and collective impact on the forecasting model's performance and.

(c) To develop a dashboard to display forecasts and analyze trends.

1.5 Scope of The Project

- Python will be used as the main tool to develop and analyze the model evaluation.
- The model performance will be evaluated by using historical weather data that had collected from Johor, Malaysia environments.

- The project will focus on constructing a hybrid model that combines the strengths of Nonlinear Autoregressive with Exogenous Inputs (NARX) and Long Short-Term Memory (LSTM) networks to forecast solar irradiance.
- The model will integrate various weather parameters which are Air Temperature, Cloud Attenuation, Precipitation Rate, Dewpoint Temperature, Surface Pressure, Precipitable Water, Relative Humidity, Wind Speed, Wind Direction

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