

**A NEURAL NETWORK BASED MODEL FOR FORECASTING
THE POWER OUTPUT OF A COMMERCIAL SCALE
PHOTOVOLTAIC POWER PLANT**

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Degree of Master of Engineering

Department of Mechanical Engineering

University of Moratuwa

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Dissertation submitted in partial fulfillment of the requirements for the
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Declaration

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Dr. Indrajith D. Nissanka

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Abstract

Solar photovoltaic (PV) is penetrating electrical grids with a substantial growth of new additions, as a result of renewable energy policies and plans implemented locally and globally. However, the intermittent nature of the availability of solar energy brings an uncertainty into electrical power systems making it complex for power management and integrating into existing electricity infrastructure. This has been a key issue in promoting renewable energy in developing countries. Accurate solar power forecasts in different time horizons can play a vital role to bring down the uncertainty by a significant margin. In this work, a neural network (NN) model was coupled with a decomposition and transposition (D&T) model to forecast day(s) ahead hourly PV output of a grid connected 1 MW solar PV plant located in Hambantota, Sri Lanka. Historical weather and solar radiation data for last 14 years were collected from two APIs (Application Programming interfaces) for the location of PV plant and variation of global horizontal irradiation (GHI) with percentage cloud cover, rain, temperature, relative humidity, and wind speed were analysed. The selected parameters from the analysis together with day and hour numbers were fed in to the NN model through a scaling layer and trained it using Levenberg–Marquardt backpropagation algorithm. Optimum NN model was selected by changing the hidden layer sizes and calculating the mean squared error. The forecasted GHI values of the optimized NN model were decomposed to diffuse horizontal irradiance (DHI) and direct normal irradiance (DNI) using Erbs correlation, as the first step of D & T model. Then, DHI and DNI components were converted to global tilted irradiance (GTI) using HDKR correlation, in order to calculate solar PV output, including possible plant specific losses. The correlation coefficient (R) between GHI output and target values of the trained NN model for an unseen testing data set was observed to be 0.86. For final model, mean percentage forecasting accuracy was observed to be 86% with 12% standard deviation. The model could be adopted to any commercial or utility scale solar PV plant which is in a tropical climate region.

Key words: Machine Learning Model, Neural Network, Solar Power Forecast, Solar PV, Utility scale power plant

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List of Abbreviations

Abbreviation	Description
ANN	Artificial Neural Network
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
BFGS	Broyden–Fletcher–Goldfarb–Shanno formula
CCGT	Combined Cycle Gas Turbine
CEB	Ceylon Electricity Board
DFP	Davidon–Fletcher–Powell algorithm
DHI	Diffuse Horizontal Irradiance
EBH	Direct Horizontal Irradiance
FFNN	Feed Forward Neural Network
GA-ANN	Genetic Algorithm-based Artificial Neural Network
GHI	Global Horizontal Irradiance
GTI	Global Tilted Irradiance
HDKR	Hay-Davies-Klucher-Reindl model
ICE	Internal Combustion Engines
IEA	International Energy Agency
IEC	International Electrotechnical Commission
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LM	Levenberg-Marquardt algorithm
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mean Error
MIT	Massachusetts Institute of Technology
MLP	Multilayer Perceptron
MLR	Multiple linear regression
MSE	Mean Squared Error
NCRE	Non-Conventional Renewable Energy

NOAA	National Oceanic and Atmospheric Administration
NOCT	Nominal Operating Cell Temperature conditions
OCGT	Open Cycle Gas Turbine
PV	Photovoltaic
RH	Relative Humidity
RMSE	Root Mean Squared Error
RNN	Recurrent neural network
SD	Standard Deviation
SE	Squared Error
STC	Standard Test Condition
STL	Seasonal-Trend decomposition procedure based on Loess
UTC	Universal coordinated Time
VRE	Variable Renewable Energies
WRC	World Radiation Center