# INTELLIGENT MODELLING FOR SOLAR ENERGY FORECASTING AND APPLICATIONS

A Thesis submitted to the
Delhi Technological University
for the award of Doctor of Philosophy
in
**Electronics and Communication Engineering**

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# DECLARATION

I Gulnar Perveen, a Ph.D. scholar, Roll No. 2K14/Ph.D./ECE/08 hereby declare that the thesis titled **"Intelligent Modelling for Solar Energy Forecasting and Applications"** which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy has not previously formed the basis for the award of any degree, diploma associateship, fellowship or other similar title or recognition.

Place: Delhi **(GULNAR PERVEEN)**

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# CERTIFICATE

On the basis of declaration submitted by Ms. Gulnar Perveen, a Ph.D. scholar, Roll No. 2K14/Ph.D./ECE/08. I hereby certify that the thesis titled **“Intelligent Modelling for Solar Energy Forecasting and Applications”** which is submitted to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy, is an original contribution with existing knowledge and faithful record of research carried out by her under my guidance and supervision.

To the best of my knowledge this work has not been submitted in part or full for any degree or diploma to this university or elsewhere.

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# ABSTRACT

Due to the growing population of the world, there is a surge in the demand for energy – specifically element energy. The production of electricity contributes the largest share in the emission of greenhouse gases that emanate from the burning of fossil fuel. So, a need has arisen for a clean form of energy i.e. renewable energy that can contribute to the increasing demand for energy worldwide. For the accurate design and development of solar energy based systems, solar radiation resource data plays a significant role. Unfortunately, the measured data is rarely available for research purpose for these stations where measurement is already being done. Therefore, it is essential to develop modelling techniques that can forecast global solar energy for such locations where measurements have not been done with reasonable accuracy. The number of mathematical models has been developed for assessment of solar energy under cloudless skies. In fact, it is rather difficult to forecast accurately the behaviour of solar radiation by using these stochastic models, as they need the bases of the precise definition of problem domains and these stochastic models were found with relatively large errors and sometimes difficult to be adopted widely. These models developed, however, are not appropriate to forecast solar energy during cloudy sky. So, fuzzy logic based model have been developed in situations when deterministic or probabilistic models do not provide a realistic description of the phenomenon under study. A lot of research has been carried out and it is observed that for modelling complex systems involving large data sets, it is difficult to maintain accuracy with so much of data sets by employing fuzzy logic approach. So, an Artificial Neural Network (ANN) models were introduced, that employ artificial intelligence techniques and are data-driven which can subsequently simulate the structure. For complex function estimation, the prediction of a number of hidden layers and hidden neurons accurately using ANN is difficult as they are large in number. Also, the training time for the conventional neural network is too large, which results in a slower response of the system. The existing neural model performs only

the operation of summation of its weighted inputs; it does not perform the operation of products on its weighted inputs. Therefore, hybrid intelligent models have been introduced for forecasting solar energy which integrates the features of fuzzy logic approach and ANN. Further, the obtained results have been implemented for short-term power forecasting in solar photovoltaic (PV) system under composite climate zone.

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## LIST OF ABBREVIATION, SYMBOLS AND NOMENCLATURE

| | |
|---|---|
| $a,b,c,d$ | regression coefficients of empirical models (dimensionless) |
| $c_a$ | average calculated value (dimensionless) |
| $c_i$ | $i^{th}$ calculated value (dimensionless) |
| $E$ | absolute error (%) |
| $e_i$ | $i^{th}$ estimated value (dimensionless) |
| $e_h$ | hourly error (hours) |
| $f_i$ | first order polynomial |
| $G_{sc}$ | solar constant ($W/m^2$) |
| $G_T$ | solar irradiance at Standard Test Condition (STC) ($W/m^2$) |
| $GW_p$ | giga watt peak |
| $H_d$ | diffuse solar energy ($MJ/m^2$) |
| $H/H_g$ | global solar energy ($MJ/m^2$) |
| $H_o$ | extraterrestrial solar radiation on horizontal surface ($MJ/m^2$) |
| $I_{pmax}$ | maximum power point current of solar PV module (A) |
| $I_{sc}$ | short circuit current of solar PV module at STC (A) |
| $kWh/kW_p$ | kilowatt hours per kilowatt peak |
| $kWh/m^2/day$ | kilowatt hour per meter square per day |
| kWh/year | kilowatt hour per year |
| L | measured data |
| $L_{max}$ | highest value of relevant set of data |
| $L_{min}$ | lowest value of relevant set of data |
| $L_s$ | normalized/scaled data |
| $m_a$ | average measured value (dimensionless) |
| $MJ/m^2$ | mega joule per meter square |

| | |
|---|---|
| $m_i$ | $i^{th}$ measured value (dimensionless) |
| $MW_p$ | mega watt peak |
| $n$ | number of observations (dimensionless) |
| $N_{OCT}$ | temperature of solar panel ($^oC$) |
| $N_{PVP}$ | photovoltaic arrays in parallel (number) |
| $N_{PVS}$ | photovoltaic arrays in series (number) |
| $O_{1,i}$ | output function for fuzzy sets $A_i$ |
| $O_{1,j}$ | output function for fuzzy sets $B_j$ |
| $O_{2,i}$ | output of $i^{th}$ node of layer 2 |
| $O_{3,i}$ | output of $i^{th}$ node of layer 3 |
| $O_{4,i}$ | output of $i^{th}$ node of layer 4 |
| $O_{5,i}$ | output of $i^{th}$ node of layer 5 |
| $P_m$ | measured atmospheric pressure (hPa) |
| $P_{max}$ | power of solar PV module at Maximum Power Point (MPP) (W) |
| $P_{m,h}$ | hourly mean values of the measured power in the *h*-th hour |
| $P_o$ | maximum possible atmospheric pressure (hPa) |
| $P_{p,h}$ | hourly mean values of the forecasted power in the *h*-th hour |
| $P_{PV}$ | power output of solar PV array at MPP (W) |
| $P_{PV,STC}$ | rated power output of solar PV system of single array at MPP (W) |
| r | correlation coefficient (dimensionless) |
| $R^2$ | coefficient of determination (dimensionless) |
| $RF_m$ | measured rainfall (mm) |
| $RF_o$ | maximum possible rainfall (mm) |

| | |
|---|---|
| $RH_m$ | measured relative humidity (%) |
| $RH_o$ | maximum possible relative humidity (%) |
| S | measured sunshine duration (hours) |
| $S_o$ | maximum possible sunshine duration (hours) |
| $T_j$ | ambient temperature around PV panels (°C) |
| $T_{amb}$/$T_m$ | measured ambient temperature (°C) |
| $T_o$ | maximum possible ambient temperature (°C) |
| $V_{oc}$ | open circuit voltage of solar PV module at STC (V) |
| $V_{pmax}$ | maximum power point voltage of solar PV module (V) |
| $w_i$ | $i^{th}$ rules strength |
| $\overline{wi}$ | normalized firing rule strength |
| $w_{ij}$ | connection weight directed from *j* neuron to *i* neuron |
| $WS_m$ | measured wind speed (Km/hr) |
| $WS_o$ | maximum possible wind speed (Km/hr) |
| $x_{ij}$ | $j^{th}$ neuron incoming signal |
| $X_{max}$ | maximum limit of normalized range |
| $X_{min}$ | minimum limit of normalized range |

**Greek Symbols**

| | |
|---|---|
| $\phi$ | latitude of the site (degree) |
| $\omega_s$ | mean sunrise hour angle (degree) |
| $n_{day}$ | number of days in a year beginning from 1st January (dimensionless) |

| | |
|---|---|
| $\delta$ | solar declination angle (degree) |
| $\eta_o$ | optical efficiency (%) |
| $\gamma$ | temperature parameter at MPP (dimensionless) |
| $\theta_i$ | bias of *i* neuron |
| $\mu_A(Y)$ | membership function of subset A of universal set Y |
| $\mu_{A,i}(x)$ | membership function degree of fuzzy sets $A_i$ |
| $\mu_{A \cup B}(Y)$ | union of fuzzy sets A and B of universal set Y |
| $\mu_{A \cap B}(Y)$ | intersection of fuzzy sets A and B of universal set Y |
| $\mu_B(Y)$ | membership function of subset B of universal set Y |
| $\mu_{B,j}(y)$ | membership function degree of fuzzy sets $B_i$ |
| $\mu_p$ | membership function |
| $\mu_p(Y)$ | grade of membership function of universal set Y |
| N | normalization to the firing strength |
| $\sum$ | summation function |
| $\cup$ | union |
| $\cap$ | intersection |

**Nomenclature**

| | |
|---|---|
| AC | Alternating Current |
| ANFIS | Adaptive Neural-Fuzzy Inference System |
| ANN | Artificial Neural Network |
| AR | Auto Regressive |
| ARMA | Auto Regressive Moving Average |
| CFNN | Cascade Forward Neural Network |
| CPCR2 | Code for Physical Computation of Radiation, 2 bands |
| CWET | Centre for Wind Energy Technology |

| | |
|---|---|
| DNI | Direct Normal Irradiance |
| EMR | Eastern Mediterranean Region |
| EMS | Energy Management System |
| ENN | Elman Neural Network |
| FCS-MPC | Finite Control Set-Model Predictive Control |
| FFNN | Feed Forward Neural Network |
| FIS | Fuzzy Inference System |
| FY | Financial Year |
| GA | Genetic Algorithm |
| GBIs | Generation Based Incentives |
| GRNN | Generalized Regression Neural Network |
| GWO | Grey Wolf Optimization |
| H | High |
| HH | High-High |
| HIT | Heterojunction with Intrinsic Thin Layer |
| IMD | Indian Meteorological Department |
| INC | Incremental Conductance |
| ISA | International Solar Alliance |
| IST | Indian Standard Time |
| JNNSM | Jawaharlal Nehru National Solar Mission |
| L | Low |
| LAT | Local Apparent Time |
| LM | Low-Medium |

| | |
|---|---|
| LNN | Linear Neural Network |
| LRNN | Layered Recurrent Neural Network |
| LVQ | Learning Vector Quantization |
| M | Medium |
| MAPE | Mean Absolute Percentage Error |
| MBE | Mean Bias Error |
| MF | Membership Function |
| MH | Medium-High |
| MLFFNN | Multi-Layer Feed Forward Neural Network |
| MNRE | Ministry of New and Renewable Energy |
| MPC | Model Predictive Control |
| MPE | Mean Percentage Error |
| MPP | Maximum Power Point |
| MPPT | Maximum Power Point Tracking |
| NAPCC | National Action Plan on Climatic Change |
| NISE | National Institute of Solar Energy |
| NIWE | National Institute of Wind Energy |
| NMAE | Normalized Mean Absolute Error |
| nRMSE | Normalized Root Mean Square Error |
| NWP | Numerical Weather Prediction |
| P&O | Perturb and Observe |
| PSO | Particle Swarm Optimization |
| PV | Photovoltaic |

| | |
|---|---|
| RBFNN | Radial Basis Function Neural Network |
| RES | Renewable Energy Sources |
| REST | Reference Evaluation of Solar Transmittance |
| REST2 | Reference Evaluation of Solar Transmittance, 2 bands |
| RMSE | Root Mean Square Error |
| SEC | Solar Energy Centre |
| SOM | Self-Organizing Map |
| SPV | Solar Photovoltaic |
| SRRA | Solar Radiation Resource Assessment |
| STC | Standard Test Condition |
| SVM | Support Vector Machine |
| SVR | Support Vector Regression |
| SVR-RBF | Support Vector Regression -Radial Basis Function |
| TRAINLM | Levenberg-Marquardt Training algorithm |
| TSK | Takagi, Sugeno & Kang |
| VH | Very-High |
| VL | Very-Low |