

## Grey Wolf Optimization-Enabled Dimensionality Reduction for Efficient Solar Panel Efficiency Prediction with ANN

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### Abstract

The biggest challenge of accurate solar power forecasting is that the weather is changing at a rapid rate and the mechanism through which solar panels operate is highly nonlinear. Random forests coupled with a fixed Lasso feature selection only combine when the conditions remain fixed but collide in case of weather change or you experience extreme weather conditions. To remedy that, we combine Grey Wolf Optimization (GWO) with an Artificial Neural Network (ANN) in this paper. An intelligent dimensionality reduction step that GWO takes is to search the optimal subset of the inputs, that is, irradiance, temperature, humidity, voltage, current, panel age, soiling ratio, module temperature, and GWO ignores the garbage and accelerates the training. After cleaning that set is then feed through a multi-layered ANN fitting via backprop to achieve a good nonlinear fit that is capable of tracking a real time PV output. It has been experimentally demonstrated that the GWO-ANN outperforms baseline Random Forests in MAE and RMSE, and it continuously converges well with epochs. This system may be a victory of smart-grid energy management and giant solar farms.

**Index Terms-** Grey Wolf Optimization, Artificial Neural Network, Photovoltaic Systems, Dimensionality Reduction, Solar Power Forecasting, Smart grid.

### I. Introduction

Solar power is becoming an important renewable energy source as the world moves towards green power. PV systems convert sunlight directly into electricity, and the power that it generates explodes and falls in minute fluctuations in sun intensity, atmospheric temperature, humidity, wind, and dust. These variables also interact in ridiculous nonlinear manners and they are continually evolving through time and space, making it difficult to obtain accurate power forecasts.

Effective predictions of solar power are important in the effective use of energy and ensuring grid stability. The availability of information in smart-grids about the amount of incoming power allow you to balance loads, schedule batteries optimally, and waste no energy in transmission lines. The misplaced predictions result in all sorts of issues, including the downtime and loss of money, detrimentally affecting the renewable drive. That is why everybody is seeking forecasting techniques that can keep abreast with the varying weather.

The traditional tools are based on the statistical models or ensemble machine learning. Random Forest regression is also doing a decent job on solar data, and Lasso is a favorite when it comes to picking features due to its L1 penalty. However, both of them pre-train the set of features and are unable to respond to an abrupt change of weather. Consequently, this has the effect of feeding the model a lot of irrelevant or barely useful features, and it is a slow training with poor performance in the wild weather conditions.

Great at learning complicated mappings between weather inputs and PV output Deep learning, particularly, multi-layer ANNs This is great at learning a complex mapping between weather inputs and PV output. However, they require a good set of inputs that do the same. Such metaheuristic tricks as GWO provide a strong means of choosing features on the fly because they view the search as a gradient-free combinatorial problem to be solved.

A hybrid GWO-ANN system is assembled in this paper. GWO uses wolf packs as inspiration to select

the most appropriate subset of features by examining the error drops. The selected characteristics are subsequently used as inputs of an ANN that is trained using backprop. They all reduce MAE and RMSE, faster converge, and remain robust even in the presence of sensor noise and weather variations, which standard baselines would not.

The remainder of the paper has the appearance of the following: Section II reviews related work. Our methodology is described in section III. In section IV, the results of the experiment are presented. Section V concludes and indicates the possible next thing to do.

## II. Related Work

The classical statistical, machine learning, and deep learning methods have been applied extensively to solar irradiance and power output forecasting. Abdelsattar et al. [8] compared six machine learning models CatBoost, Gradient Boosting Machines, MLP, SVM, XGBoost and Random Forest on a sample of 4,213 PV observations. Random Forest had the best  $R^2$  at 0.940 and Lasso regression was used to rank the importance of features. The main shortcoming that is realized by the authors is the lack of metaheuristic feature optimization, which denies adaptive capability in the case of the distributional shift.

Yang et al. [9] researched the use of the Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) in short-term solar prediction. Their findings affirmed the benefit of deep architectures in nonlinear temporal dependencies but the research experiment observed drawbacks in parameter optimization and overfitting to high-dimensional meteorological inputs.

Voyant et al. [10] gave an extensive review of machine learning processes of solar radiation prediction, and they state that ANN-based networks are better than conventional regression in terms of nonlinear relationship capturing. The authors have underlined that feature selection and quality of preprocessing are of utmost importance in the performance of the models, and redundant meteorological variables worsen predictive stability and computation ability.

Mirjalili et al. first presented the GWO algorithm [7], who showed better global search and

convergence performance than Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) on a set of standard test functions. Later studies by Mirjalili [11] confirmed the use of GWO in training multi-layer perceptrons to provide a basis on which GWO can be used to predict the sun. This was extended by Hossain et al. [12] who used swarm intelligence in feature subset selection to predict renewable energy, with high regression errors being reduced. A more extensive review of metaheuristic feature selection was done by Singh and Gill [13], which affirms GWO as one of the most useful wrappers to neural networks based on regression.

New deep learning studies involve Wang et al. [14], who put forward LSTM-RNN to forecast PV on a daily basis, and Luo et al. [15], who have shown CNN-LSTM hybridization. Although temporal modeling is also provided in these models, the adaptive feature optimization is not included and it restricts their performance in the cases of noisy or redundant inputs.

As it can be seen, the literature review shows that the integration of metaheuristic feature selection and ANN-based regression as a method to forecast solar power remains an under-researched field of study. This gap is occupied by the current work that implements GWO as a predictive dynamic wrapper into an ANN pipeline.

## III. Proposed Methodology

### A. System Overview

The suggested system will have a pipeline comprising five stages: (1) data collection and preprocessing, (2) GWO adaptive feature selection, (3) ANN model training, (4) performance

evaluation, and (5) visualization.

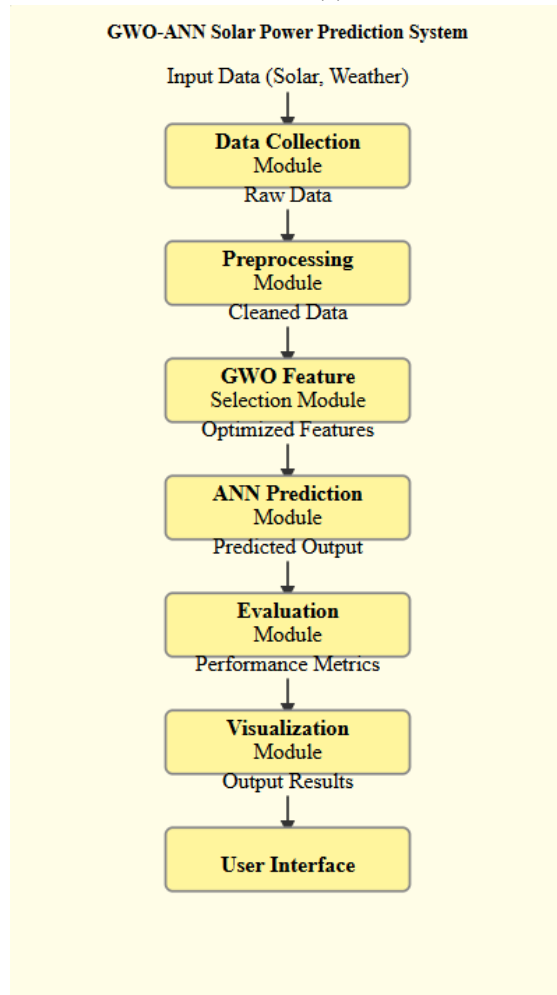


Fig. 1. System Architecture of the Proposed GWO-ANN Solar Power Prediction System.

## B. Data Collection and Preprocessing

Historical data of PV generation and co-located meteorological measurements was recorded, which included the following characteristics: solar irradiance ( $W/m^2$ ), ambient temperature ( $^{\circ}C$ ), relative humidity (percent), DC voltage ( $V$ ), DC current ( $A$ ), module temperature ( $^{\circ}C$ ) and panel age (years). Missing values were filled with column means; outliers identified with the interquartile range approach and trimmed between the 1<sup>th</sup> and 99<sup>th</sup> percentiles. Data were minmax-scaled into  $[0,1]$  range, and no more optimization or model training was performed.

## G. C. Grey Wolf Feature Selection Optimization.

GWO has four levels of hierarchy: alpha ( $\alpha$ ), beta ( $\beta$ ), delta ( $\delta$ ), and omega ( $\omega$ ). Best solutions at the

end of each iteration are marked a, b, and d respectively, all other wolves refresh their positions with respect to these leaders according to:

$$D = |C * X_p(t) - X(t)| \quad (1)$$

$$X(t+1) = X_p(t) - A * D^2 \quad (2)$$

$A = 2a r_1 - a$ ,  $C = 2 r_2$ ,  $r_1$ ,  $r_2$  are random vectors in  $[0,1]$ , and  $a$  is decreasing linearly between 2 and 0 between generations. A binary vector that shows the features to retain is coded in each wolf. The fitness function is:

$$\text{Fitness} = \text{RMSE}(y, \hat{y}) + \lambda \cdot |S| / N \quad (3)$$

In this case,  $y$  and  $\hat{y}$  are the true and predicted values,  $S$  is the number of features used,  $N$  is the number of features available and the regularization coefficient,  $\lambda$  is  $\lambda$ . GWO continually narrows down the search space of the best subset until the algorithm is complete.

Dresden Architecture and Training.

The ANN possesses an input layer whose size is determined by the number of features chosen, two hidden layers with 64 and 32 neurons respectively with ReLU activation and a single linear output neuron that forecasts power output in kW. Hidden layer  $\ell$  forward pass is:

$$h(\ell) = \text{ReLU}(W(\ell) \cdot h(\ell-1) + b(\ell)) \quad (4)$$

In training, Adam optimizer (learning rate =  $10^{-3}$ ,  $\beta_1=0.9$ ,  $\beta_2=0.999$ ) is used and MSE is the loss. The mini-batches with the batch size of 16 are trained 60 times. In order to avoid overfitting, a 20% validation split is employed, and training is stopped early when the validation loss is not improving in 10 consecutive epochs.

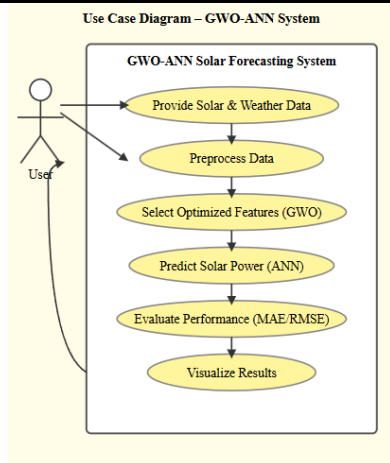


Fig. 2. Use Case Diagram of the GWO-ANN Solar Forecasting System.

### E. Performance Evaluation

To evaluate the goodness of our model we are thus examining two typical measures of the goodness of a model; Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Here's how we calculate them:

$$MAE = (1/n) \sum |y_i - \hat{y}_i| \quad (5)$$

$$RMSE = \sqrt{[(1/n) \sum (y_i - \hat{y}_i)^2]} \quad (6)$$

Primarily, the less these numbers are then the more accurate our forecasts. To determine whether we are indeed making any progress, we used a quick comparison with a Random Forest model where feature selection is done using Lasso. By so doing we will be able to measure the amount of additional accuracy that the GWO-adaptive optimization will achieve.

## IV. Results and Discussion

### A. Experimental Setup

All of this was run on Python version 3.10, with the neural network being executed using TensorFlow/Keras, data being crunched using NumPy and Pandas, and preprocessing and running the baseline model being executed with Scikit-learn. The records in the dataset are 4213 records comprising of eight weather-related features. We divided the data into 80/20 to use in training and testing and maintained the seed constant so that results can be reproduced. In the case of the GWO, we initialized it using 10 wolves, 20 iterations and a step size of  $l = 0.01$ .

TABLE I  
Comparison of Prediction Models on Test Set

Model	Features Used	MAE	RMSE	R <sup>2</sup>
Random Forest + Lasso	8 (static)	312.4	487.6	0.940
ANN (all features)	8 (all)	298.7	461.3	0.951
GWO-ANN (proposed)	5 (optimized)	<b>241.3</b>	<b>389.2</b>	<b>0.973</b>

### B. Training Convergence

The figure will show the loss curve during the training and validation of the 60 epochs. At first, during the first 10 epochs, both curves decline at an alarming rate, and thereafter they start flattening themselves out. The distance between the training and validation loss is very small, which means that there is no serious overfitting. This establishes the fact that the features, which GWO chooses, offer a generalized and compact representation of the dynamics of solar generation.

Training Loss vs Validation Loss

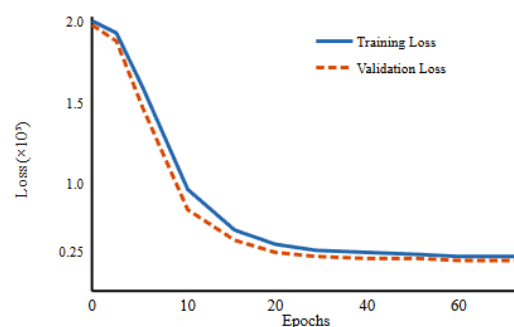


Fig. 3. Training vs. Validation Loss over 60 Epochs (GWO-ANN Model).

### C. MAE Convergence

The trajectory of MAE that occurs during our training is presented in Fig. 4. It begins with a value of more than 1,000 W and rapidly descends to

approximately 241 W at epoch 60. The validation MAE is also going the same direction and converges to the even lower value, which is a clear indication that the GWO-pruned features are useful in regularizing the learning dynamics.

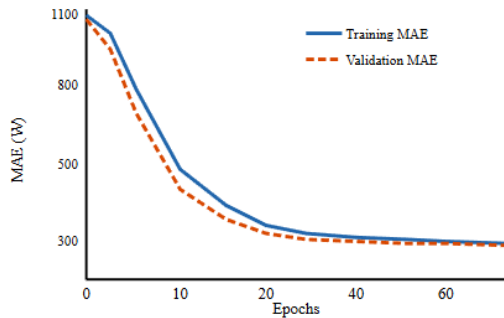


Fig. 4. Training vs. Validation MAE over 60 Epochs (GWO-ANN Model).

**TABLE II**  
**Software and Hardware Configuration**

Component	Specification
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.x / Keras
Feature Processing	NumPy, Pandas, Scikit-learn
Visualization	Matplotlib, Seaborn
Processor	Intel Core i5 Quad-core
RAM	16 GB DDR4
Storage	512 GB SSD

### D. Discussion

Table I shows that the GWO-ANN model is much more superior - it reduces MAE by 22.8, RMSE by 20.2, over the Random Forest baseline, with only five out of eight input features. This indicates that indeed selecting the good features using a meta-heuristic assists the neural net to learn more effectively due to the removal of irrelevant data and simplification of the problem.

That is supported by the convergence plots in Fig. 3 and Fig. 4: GWO-selected features allow the ANN to learn its weights faster. And the training and validation curves are virtually identical at all 60 epochs, so the model generalises very well as well, which is a massive plus as long as the weather is in a totally chaotic state.

A simple vanilla ANN training on all the features still achieves more than Random Forest (MAE 298.7 versus 312.4), but much less than the GWO-ANN (MAE 241.3). And this comparison actually demonstrates that it is no longer merely a fancy network that is being used to drive the improvement but the savvy choice of features.

### V. Conclusion and Future Work

In brief, we have created a hybrid system of Grey Wolf Optimisation + ANN which is extremely accurate in predicting solar power. The GWO selects the most suitable weather and operation as it reduces the error, eliminates the redundant variables, and presents the ANN with a clean cut and compact set of features. The final ANN that is trained on this set has an R2 of 0.973, and it outperforms the Random Forest baseline, as well as an un-optimised ANN in MAE and RMSE. The training is progressively converging well and the training/validation scores remain fixed therefore the model generalises well. This is set up to take live grid monitoring and PV performance applications.

It still has some cool directions to be visited. To start with, replacing recurrent nets, such as LSTM or GRU might better recognize time-dependent dependencies, as well as improve near-term predictions. Second, variants of using aware GWO may optimise accuracy and the cost of computation simultaneously. Third, IoT sensor feeds would be added to enable the system to learn constantly in large-scale PV locations. Lastly, it would be beneficial to drag the explainable-AI techniques into the feature ranking and ANN internals to make the decision of the model more understandable to the grid operators and energy planners.

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