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Solar Power Prediction by Artificial Immune Algorithm for Environmental Features Selection

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Abstract- The growing penetration of renewable energy resources poses a high degree of uncertainty in the electric grid's behavior due to the intermittent nature of such resources. Handling the uncertainty becomes even more challenging when it is extended to the loads as well. Hence many of researchers work for this to predict the power of the solar panel plates. This paper has developed a model that identifies the features of the environment that affect the [solar power generation in terms of ratio. Artificial Immune System based Solar Power Prediction model finds the features and ratio that directly contribute the solar power in particular geographical location. Expeirment was done on real dataset of India geographical data. Result shows that proposed model has increases the evaluation parameter values as compared to previous models.

Keywords- Weather Feature Selection, Hybrid Prediction Method, PV Power Forecasting.

I. INTRODUCTION

The consumption of energy in today's world is one of the most reliable measures of a nation's level of development. The most industrialised and energy-consuming nations continue to rely on energy as a driver of growth and economic development. These nations are also among the most energy-intensive.

Its effect on all of the other industries in which it makes activity possible means that its contribution to the creation of national wealth is not restricted to its own added value but encompasses the entire economy. Because of the significant financial importance of investments in this sector and the length of time over which they are held, the future landscape of the energy industry will be shaped by the strategic decisions made today. In addition, the greenhouse gas emissions that the world has been exposed to for the past few years have reached a level that our planet can no longer physically withstand.

Damage that cannot be repaired would be caused by climate change as well as the disruption of many ecological balances. As a result, we are in the position where we need to put into place sustainable policies that include all three of the following aspects: the economic, the social, and the environmental [1].Solar and wind power account for the majority of the world's consumption of renewable energy sources [2]. It generates clean and climate-friendly electricity, jobs, and reduces risks on multiple levels, such as exposure to particles and susceptibility to the prices of imported fuels. Additionally, it generates clean and climate-friendly electricity. When compared to the high cost of power generation, the cost of generating electricity using wind power is significantly lower when analysed using the same parameters as those used to evaluate other technologies. This is primarily due to the extremely beneficial effect that it has on the native population.The hybrid energy conversion system, also known as HECS, [3] makes reference to the generation of electricity from multiple sources. It combines a variety of sources that are renewable. The fact that HECS does not rely on just one source for its energy means that it can function adequately regardless of the weather. This is the system's primary benefit. Both a connection to the power grid and independent operation as a microgrid are viable options for HECS [3, 4].

Dust, wind, the temperature and humidity of the surrounding air, and ambient air all have an effect on solar systems. It has been observed that the surface temperature of PV panels increases as a result of dust collecting on the surface of the panel [5]. [Citation needed] On the other hand, there is not a great deal of research that has found a robust correlation or causation linking humidity and either the performance of the panels or the temperature of the panels.

The amount of moisture in the air, which can be measured as humidity, has the ability to scatter incoming light [6]. As a direct consequence of this, a lesser amount of effective solar radiation will reach the surface of the PV panel. Because of this, photovoltaic (PV) systems that operate in damp areas may have a lower overall efficiency. Data on the global solar radiation must typically be a primary requirement [7] before a solar photovoltaic (PV) system can be designed for a particular region. The criteria for the data are that it needs to be suitable for the technology and observations made in recent times, that it needs to be reliable and fit for the design and performance optimization of solar technologies for any region, and that it needs to meet all of these criteria. The measurement of solar radiation is typically not available in every part of a region because it is impractical to transport, calibrate, and maintain measurement apparatus on a regular basis in every part of the region. Therefore, estimation strategies and methodologies are utilised in order to project and forecast the parameters for various regions without actively taking direct measurements. This is accomplished through the utilisation of appropriate approximation models [8].

II. RELATED WORK

A state-of-the-art review of hybrid meta-heuristic algorithms that were applied in order to determine the optimal size of HRES is presented by Bouaouda, A. et al. in [9]. The primary focus of this section is on the relevant literature sources and the distribution of those sources. The next thing we do is review the previous research from two different perspectives, including the currently applied hybrid meta-heuristic algorithms for both single-objective and multi-objective design.

The goal of the grid-to-vehicle optimization approach proposed by Agrawal, H. et al. in [10] is to integrate electric vehicles with the grid as a backup source of energy. This will be accomplished through the reduction of active and reactive power losses as well as the maintenance of the voltage profile. In this article, we will go over three different case studies: I the integration of renewable energy sources by themselves; (ii) the integration of electric vehicles by themselves; and (iii) the hybrid mode integration of renewable energy sources and electric vehicles.

Han et al. (2019) [11]. These researchers examined the compatibility of different types of power generation by contrasting the fluctuations and ramp rates of individual power generation (IPG) with those of combined power generation. Wind, solar, and hydropower all contributed to their findings (CPG). The methodology was evaluated by applying it to a region in China as a case study, and the results indicate that complementarity can be improved by adjusting the proportion of solar power to wind power.

Berger et al. (2018) [12] propose the concept of critical time windows for the purpose of the systematic evaluation of energetic complementarity across both space and time. Critical time windows are periods within the time series that have low average capacity factors and they represent those periods. While preserving the chronological order of the events, the accurate description of extreme occurrences within the time series is provided by these critical time windows. These authors also propose a criticality indicator that quantifies the fraction of time windows during which generation from variable renewables is below a certain threshold. This criticality indicator will allow for a comprehensive evaluation of energetic complementarity at the various locations over arbitrary time scales.

Risso and Beluco (2017) [13], proposed a method for performing a graphical representation of temporal complementarity of resources at different locations, by means of a chart of complementarity as a function of distance, using a hexagonal cell network for dividing the case study region. This chart was used to perform the graphical representation of temporal complementarity of resources at different locations. The method was expanded in a subsequent paper (Risso et al., 2018), and the graphical representation is now depicted as complementary roses. The length of the petals denotes the distance to another cell, and their colour denotes the degree of energetic complementarity between these cells.

In the research paper that Berger et al. (2018) [13] published, the authors demonstrate how low wind power production events can be compensated for on a regional scale by making use of the various wind patterns that can be found across the region (western Europe and southern Greenland in their case study). Their findings provided evidence that wind power production on different continents might reduce the number of events with low wind power production, which made a case for evaluating the potential benefits of intercontinental electrical interconnections. [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Cit

Yordanos et. al. in [14] This study presents a method for forecasting the hourly mean PV power generation one day in advance using a combination of genetic algorithms (GA), particle swarm optimization (PSO), and adaptive neuro-fuzzy inference systems (ANFIS). An integrated hybrid algorithm that combines GA and PSO is used to optimise an ANFIS-based PV power forecasting model for the plant. A Binary GA with a Gaussian process regression model based fitness function is used to determine important input parameters that significantly influence the amount of output power of a PV generation plant; and an integrated hybrid algorithm that combines GA and PSO is used to determine important input parameters that significantly influence the amount of output power of a PV generation plant. The power generation data obtained from the Goldwind microgrid system located in Beijing is used to test the viability of the modelling technique that has been proposed.

III.PROPOSED METHODOLOGY

The forecasting of solar power is extremely sensitive to the state of the surrounding environment. This work centres on the selection of environmental factors that have a significant impact, such as (air, humidity, temperature, sky condition, etc.). The entire piece of work was broken down into two distinct sections, the first of which predicts feature ratios through the application of an artificial

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immune system algorithm. whereas the second module will predict the amount of solar power based on the environmental parameters that will be applied in the same ratio as the first module did. Figure 1 displays the block diagram of the entire work that was done on the Artificial Immune System-based Solar power Prediction (AISSPP). The AIS Algorithm was utilised in this model in order to select the value of the weather feature set. In this particular piece of research, an AIS genetic algorithm is utilised because it involves two stages of population updation. The primary goal of this model is to establish a proportional equilibrium between the various environmental parameters.

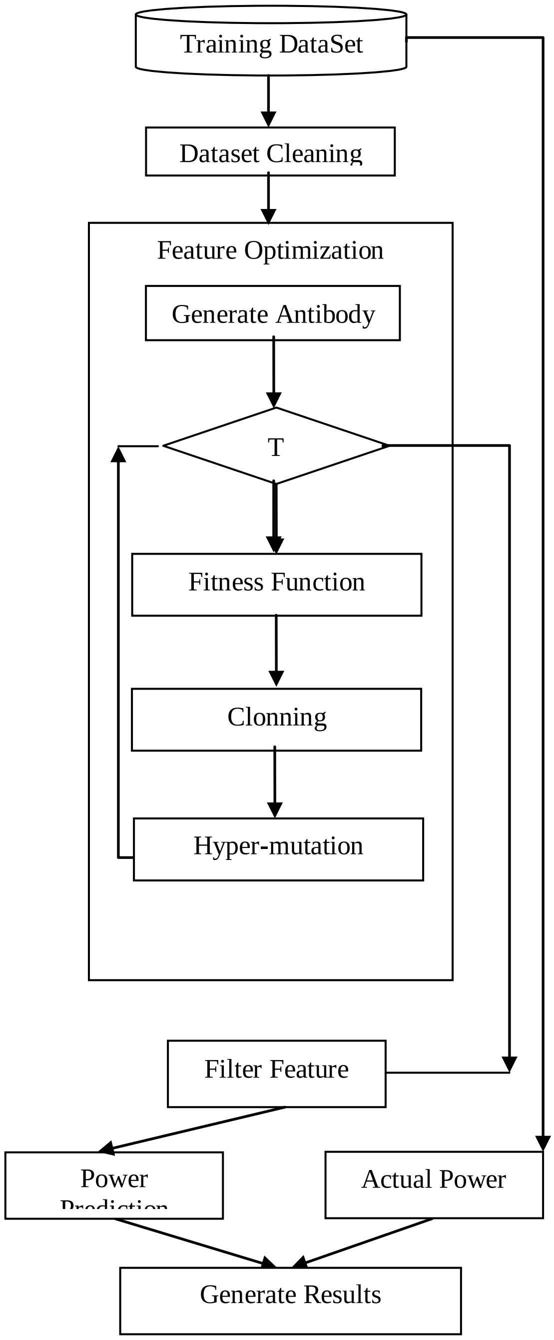

Fig. 1: Block diagram of AISSPP genetic algorithm.

Generate Antibodies: This step involved the generation of multiple chromosome sets, each of which had an environmental feature ratio that ranged from 0 to 1. This can be interpreted to mean that if the value of any feature is 0, then that feature is not being considered.

Therefore, each individual environmental feature set functions as a chromosome, and the collection of all feature sets is referred to as the population. It is possible to make the assumption that this is the case by writing the chromosome set as let Cc = [Cc11, Cc12,.... Cc1m], where m is the number of features contained in a set. P equals [Cc1, Cc2,......Ccn], where n is the total number of antibodies.

$$P \leftarrow \text{Random}(n, m) \text{ ---------(1)}$$

Table 1 Notation used in work.

Symbol	Meaning
A	Solar Panel area in m^2
γ	Solar Panel Yield Efficiency
I_r	Irradiance Watt/m square
A^T	Ambient Temperature (^oC)
Cc	Genetic Algorithm Chromosome
σ	Solar Module Efficiency
β	Maximal Power Temperature Coefficient
F	Environmental Feature Set
C^T	Nominal Operating Cell Temperature C
I	Overall insolation
W	Wind Speed at 10 m height above ground level + Wind Speed at 50 m height above ground level in m/sec
T	Temperature Range at 2 m height above ground level + Earth Skin Temperature (C)
T_c	Cell Temperature (^oC)
P_r	Surface Pressure (kPa)
P_s	Solar Panel Power (W)

Affinity

The affinity of the antibodies that were found in the population was estimated by creating a temporary random forest based on the characteristics that were discovered. According to the trained random forest model, intrusion detection was carried out in order to estimate the level of accuracy. The affinity of the antibody is what determines the accuracy value of the correct intrusion class detection. The random forest heading of this section contains more information about the training of the model. In this step, the best solution from the population set is chosen, and the environmental data from earlier years are utilized in order to calculate the power from the current ratio using the equations 2 to 4.

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$$[I\ W\ T\ P_r] = Cc*F\text{---------}(2)$$

In equation 2, Cc denotes the chromosome that possesses the ratio of m values, and F denotes the average values of m feature that are obtained from the environmental dataset. It provides an I, W, T, and Pr output, each of which is a summation of features that are of a similar type as those found in F. The next step is to obtain values for [I W T Pr] by combining aspects that are similar into a group.

$$I = SUM(Z[1:4])$$
$$W = SUM(Z[5:6])$$
$$T = SUM(Z[7:8])$$
$$P_r = SUM(Z[9])$$

Since C1, C2, C3,,, CT, and AT are constants, the values that were obtained from the previous equation can be used in step 3 to calculate Tc. The following table displays the values that were utilised throughout this work for the various constants.

$$\mathbf{T_c = T + \left[\left(\frac{I}{I_r}\right)(C^T - A^T)\frac{C_1}{W}\left(1 - \frac{\sigma}{C_2}\right)(1 - \beta) \times C_3\right]}\text{--------}(3.3)$$

$$P_s = A \times \gamma \times T_c \times P_r\text{---------}(4)$$

The results of equation 2 are used in the third equation, which was derived from equation 17 and provides a temperature value for the cell. CT is the nominal operating cell temperature that is used in equation 3.3. c1, c2, and C3 are constants whose values range between 0 and 1, and C3 can range anywhere from 5 to 45. Equation 4 [18, 19] calculates the power produced by a solar panel with the given surface area A and yield efficiency.

Cloning

The best solution, ab, is obtained by ranking the antibodies in the population according to their affinity values. As determined by the best antibody Ab feature set, a select few statuses underwent a random change. Cloning of the model can be accomplished by changing the feature status from present to absent or absent to present. The best solution, denoted by the identifier cclocal best antibody, is chosen using the fitness value. Following the sorting process, the top possible solution will undergo cloning to produce additional possible solutions. Now that an antibody has been chosen, it will clone with another possible antibody called Ccantibody,i by exchanging the environmental ratio that is currently present in the best antibody in the area. In order to carry out a cloning operation, the random position weather feature value is taken from the chromosome containing the best antibody from the local area. After that, it is transferred to the other parent antibody so that the cloning operation can continue. This results in an overall improvement to the population.

$$Cc_{new,i} \leftarrow Cloning(Cc_{antiody,i}, Cc_{local\_best\_antibody,i})\ i \in \{1,2,\ldots\ldots m\}\text{---------}(5)$$

Where Cnew,i is the updated value.

Hypermutation: The clones are then put through a hypermutation procedure, in which they are mutated in an inverse proportion to their affinity. This means that the clones of the antibody with the highest affinity are subjected to the least amount of mutation, while the clones of the antibody with the lowest affinity are subjected to the most amount of mutation. After that, the clones and the antibodies that were originally attached to them are analysed, and the N antibodies with the highest quality are selected for the subsequent iteration. There are three possible distributions for the mutation: uniform, Gaussian, or exponential.

Solar Power Prediction: During this phase, features of the geographical location were analysed to determine the level of solar power that could be expected there. The obtained value is then used in equations 3 and 4, where it is multiplied by the feature ratio and the environmental values.

IV. EXPERIMENT AND RESULTS

Simulation Environment

The MATLAB tool is used to implement each and every algorithm as well as measure of utility. The simulation is carried out on a computer with a 2.27-gigahertz Intel Core i3 processor, 4 gigabytes of random access memory (RAM), and Windows 7 Professional as its operating system. In order to evaluate how well the algorithm performs in relation to the objectives, we use four benchmarks, namely RSME, MAE, the correlation coefficient, and execution time.

Results

Table 2 MAE Based Comparison between AISSPP and BA-PSO and GA-PSO-ANFIS.

Months Year 2018	AISSPP	GA-PSO-ANFIS[14]
Apr-Jun	2183.9	17649
Jul-Sep	4707.5	88386
Oct-Dec	4810.6	9209

It can be seen from Table 2 that AISSPP performs better when compared to GA-PSO-ANFIS [14], in terms of the MAE evaluation parameters. Since the AISSPP genetic algorithm has already performed two types of learning, the first of which was the cloning of an antibody, and the second of which was hypermutation, the results have improved.

Table 3 RMSE Based Comparison between AISSPP, and GA-PSO-ANFIS.

Months Year 2018	AISSPP	GA-PSO-ANFIS [14]
Apr-Jun	2287.7	27740
Jul-Sep	4782.3	87732
Oct-Dec	5769.53	9828

It can be seen from looking at table 3 that when comparing GA-PSO-ANFIS [14] to AISSPP, the latter performs significantly better in terms of RMSE evaluation parameters. Because the AISSPP genetic algorithm used the solar angel feature in conjunction with the environmental ratio parameters, the results are significantly improved.

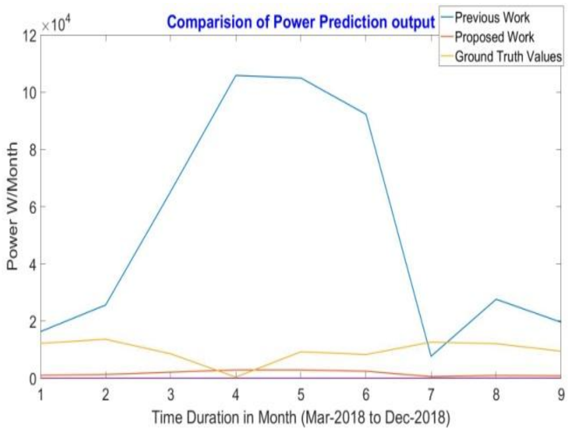

Fig. 2 Power prediction based comparison.

Table 4 Execution time Based Comparison between AISSPP and GA-PSO-ANFIS.

Iteration	AISSPP	GA-PSO-ANFIS[62]
10	1.0387	1.8765
20	1.3376	3.0678
30	1.789	3.7803

In terms of the execution time evaluation parameters, Table 4 reveals that AISSPP is superior to GA-PSO-ANFIS [14]. This is the conclusion that can be drawn from the comparison. Because the AISSPP genetic algorithm has decreased the feature set ratio between 1 and 0, selecting parameters values now produces significantly better results.

Table 5 Environmental variable ratio comparison of GA-PSO-ANFIS, and AISSPP

Feature Name	AISSPP	GA-PSO-ANFIS
Clear Sky Insolation Clearness Index	0.130	1
All Sky Insolation Incident on a Horizontal Surface	0.2800	0
Insolation Clearness Index	0.30	1
Clear Sky Insolation Incident on a Horizontal Surface	0.34	1
Wind Speed Range at 10 Meters above ground level m/sec	0.07	1
Wind Speed Range at 50 Meters above ground level m/sec	0.32	0
Temperature Range at 2 Meters above ground level degree C	0.26	1
Earth Skin Temperature Degree C	0.44	1
Surface Pressure kPa	0.48	1
Solar Insolation for fix plate	0.54	1

It can be seen from table 5 that the AISSPP feature selection ratio took into account all of the environmental parameters for solar panel power prediction. Although the selection of certain features was done in GA-PSO-ANFIS [14], which makes the model less accurate.

V.CONCLUSION

This paper has developed a model that predicts the solar power plant power as per feature feature. For estimating the environmental affecting features proposed modle has utilized the artificial immune system genetic algorithm. This algorithm dynamically adopt the parameter values without any prior training. Expeirment work was done on data obtained from India geographical location with known power of different months. Result shows that proposed modle has improved the work performance of by reducing the power prediction RMSE by 89.84% and MAE by 89.75% as compared to previous existing models. In future scholars can adoptthis method to predict the wind power.

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