Development of Hybrid Model based on Artificial Intelligence for Maximizing Solar Energy Yield

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Abstract: This paper presents an approach that utilises artificial intelligence to maximise the potential of solar energy. The proposed method involves a hybrid intelligent system that combines machine learning and genetic algorithms. The primary objective is to optimise the solar energy yield by accurately estimating global solar radiation on a horizontal surface. Four different machine learning techniques are employed for the estimation of global solar radiation. These techniques utilise measured data obtained from a local weather station to develop predictive models. The most accurate model is selected to design the fitness function for optimising the tilt angle of the solar collector. The aim is to maximise energy yield by determining the optimal angle using a genetic algorithm. Results show that the proposed model effectively identifies the daily optimal angle for maximising solar radiation on the tilted surface. The developed model demonstrates an increase in global solar radiation on a tilted surface compared to the optimal angle model commonly used in practical applications.

Keywords: Machine learning, Genetic algorithm, Hybrid system, Measured data, Solar radiation prediction, Optimal tilt angle.

1. Introduction

Solar energy, a vital renewable resource for meeting electricity demands worldwide, necessitates accurate solar radiation data to assess its applicability in diverse applications. Satellite and location-specific measurements supply solar radiation data, while meteorological data provide essential insights into radiation parameters and weather conditions. Due to inaccurate measuring equipment and inadequate maintenance, solar radiation data are missing or not sufficiently accurate in many developing countries. In those cases, theoretical and computer models are useful tools for predicting and estimating global solar radiation at a specific region.

The most common approaches for predicting solar radiation encompass stochastic methods, statistical techniques, and machine learning (ML) algorithms, which heavily rely on in-situ observed data (Mellit & Kalogirou, 2022). Lima et al. (2021) showed the comparison between and verification of two ML techniques, Deep Learning (DL) and Support Vector Regression (SVR), for solar prediction in Spain. Through a research case using actual data, Narvaez et al. (2021) demonstrated an approach based on ML algorithms that uses the best data sources from satellite and in-situ measurements and generates extremely accurate DL-based solar radiation models on the improved data. Olatomiwa et al. (2015) used a set of recorded meteorological data from a meteorological station in Iseyin, Nigeria, to assess the precision of an adaptive neuro-fuzzy inference system (ANFIS) for predicting solar radiation. Also, Quej et al. (2017) evaluated the performance and validity of three soft computing algorithms, including ANFIS, Artificial Neural Network (ANN), and Support Vector Machine (SVM), for forecasting daily horizontal global solar radiation from recorded meteorological parameters in the Yucatán Peninsula, Mexico. Pereira et al. (2022) developed a method for evaluating regional solar resources in Évora, Portugal, by utilizing numerical weather prediction and ANN models, which are based on commonly available meteorological data and solar radiation intensity.

Apart from solar radiation intensity, the tilt angle significantly influences the efficiency of the collector as increased exposure to direct sunlight improves performance. Due to the variability of meteorological and geographic factors, researchers emphasized that the optimal tilt angle is site-specific and requires thorough investigation using long-term observational datasets.

Different AI techniques can be used to calculate the optimal tilt angle of the solar collector. Datta, Bhattacharya & Roy (2016) modelled and optimized the tilt angle on a monthly basis using genetic algorithms (GA). By calculating changes in the declination and position of the sun during the day, the location, and the components

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of solar radiation, Yassir (2019) used GA to optimize the monthly direction and the angular position of the solar collector in Lhokseumawe, Indonesia. In order to determine the optimal solar tilt angle, Kim, Han & Lee (2020) developed five forecasting models utilizing Linear Regression (LR), Least Absolute Shrinkage and Selection Operator (LASSO), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB). Kulkarni et al. (2021) developed a ML model that compares various environmental parameters in order to determine the solar ideal inclination angle.

The integration of AI and optimization techniques is crucial for addressing dynamic and uncertain situations in solar systems, due to various influencing parameters. Hybrid intelligent systems are relatively unexplored, according to a literature review.

Previous researches have been oriented towards the individual use of some artificial intelligence techniques with the aim of developing predictive models of satisfactory accuracy. Also, previous research demonstrated the application of optimization techniques with the use of robust mathematical formulas as an objective function.

The aim of this paper is to present a methodology that optimizes the angle of the solar panel with the goal of maximizing the yield of solar energy, without the knowledge of a robust mathematical equations. This methodology promotes an approach where it is necessary to enter the number of the day in a year, location and meteorological parameters, and the output from the developed intelligent system is the optimal value of the angle. The basis of the developed methodology is a hybrid intelligent model that includes the coupling of one of the ML techniques and the genetic algorithm as an optimization technique.

This paper presents the application of four distinct ML techniques, namely Support Vector Machine (SVM), Regression Trees (RT), Gaussian Process Regression (GPR), and Artificial Neural Network (ANN), for the estimation of daily global solar radiation on a horizontal surface.

Solar radiation on a horizontal surface is one of the components found in the final equation for solar panel surface radiation. There is no explicit mathematical equation for solar radiation on a horizontal surface. Therefore, it is modelled with several ML techniques, and the most successful one is used in the further research. The second part of the research is represented by angle optimization using GA, with the employment of a predictive ML model within the objective function.

The research and methodology presented in this paper is of particular importance for locations that do not have expensive measuring stations, and which, therefore, can measure only the basic meteorological parameters.

In addition to the introduction section part, the paper contains several sections with a clearly defined structure. Section 2 contains the formulation of the research problem with a clear flow of activities. Section 3 presents solar radiation prediction using several machine learning techniques. The optimization of the solar collector angle based on the application of the genetic algorithm is presented in Section 4. Concluding considerations are given in Section 5.

2. Research Problem Formulation

The capability to calculate global solar radiation is crucial for solar system analysis. It is difficult to predict solar radiation, since it depends on numerous factors, particularly meteorological parameters.

The analysis of different parameters is needed to obtain an accurate prediction of solar power generation. Due to the varying incidence angle of the sun, orientation and tilt angle have an impact on the amount of solar energy that reaches the collector. The optimal collector tilt angle that is related to the horizontal plane provides the highest solar radiation to the tilted collector surface, over a certain period of time. To achieve maximum energy generation, it is crucial to keep the solar collector at an optimal slope throughout the year. The suggested research methodology which includes maximizing the daily yield of solar energy and determining the optimal angle of the solar collector using combined methods of AI is shown in Figure 1.

Therefore, the rectangle input data in Figure 1 includes inputs defined by the user. Based on them, the values of the variables found in the final mathematical formula for solar radiation on the

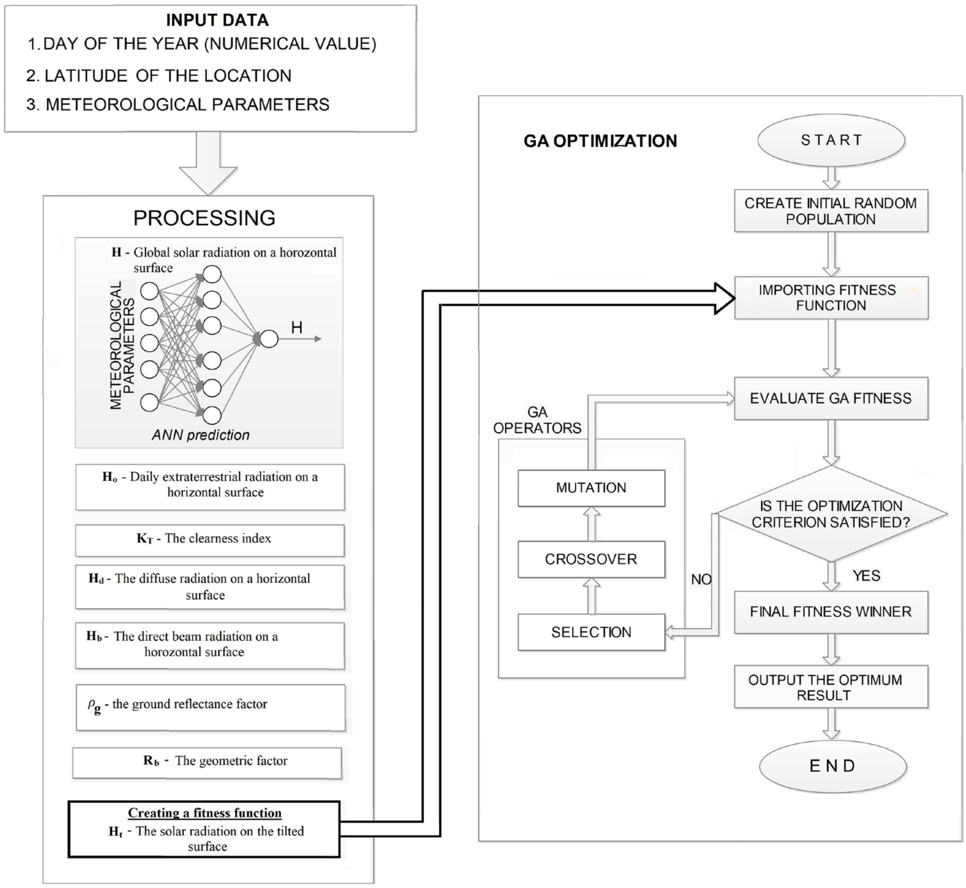


Figure 1. A flowchart outlining the proposed research methodology

tilted surface are calculated. That part belongs to the rectangle processing in Figure 1. Mathematical equations were used to calculate some values, and machine learning was also used for obtaining some values, specifically for global solar radiation on a horizontal surface. The last step in the processing is to create the final equation for the solar radiation on the tilted surface. That mathematical equation is a function of the angle and represents the objective function for the optimization process that takes place in the rectangle GA optimization.

By leveraging ML algorithms, the model aimed to capture the relationship between the input variables, i.e., meteorological parameters, and the output variable, i.e., global solar radiation, on a horizontal surface. On the basis of the root mean square error (RMSE) and the linear regression coefficient (LRC), the performance of all models with regard to global solar radiation is compared. After the ML phase, the model is further enhanced and integrated with GA technique.

The research aimed to determine the optimal tilt angle for maximizing solar radiation on a tilted surface. The mathematical model used in the optimization process considered the components of global solar radiation, including beam, diffuse, and ground-reflection radiation. However, due to the highly nonlinear relationship between the tilt angle and the total amount of solar energy received, traditional mathematical programming methods were unable to provide precise solutions for this optimization problem.

The research utilized an evolutionary GA, in order to optimize the daily tilt angle of a solar collector. By leveraging the ability of GA to explore a wide range of potential solutions and converge towards an optimal or near-optimal solution over time, the study successfully approximated the best tilt angle that maximizes solar radiation on the surface of the collector. This approach was particularly valuable as it addressed the nonlinearity of the problem, where small changes in the tilt angle can significantly impact solar energy capture. By employing the GA, the research was able to overcome this complexity and come to an efficient and effective solution to enhance the energy conversion efficiency of the solar collector.

3. Machine Learning Prediction of Solar Radiation

The selection of measured parameters for AI-based solar radiation prediction depends on factors like application, data availability, and desired prediction accuracy, and using multiple parameters in combination often proves advantageous in enhancing prediction accuracy.

In order to accurately assess the intensity of solar radiation, it is necessary to define the parameters that determine the position of the sun at a specific location. These parameters include solar radiation at the top of atmosphere of the Earth, i.e., extraterrestrial radiation, the declination of the sun δ and the solar hour angle ω_s. The daily values of these parameters can be calculated from the following equations (Duffie & Beckman, 2013):

$$H_o = \frac{24 \cdot 3600}{\pi} G_{sc} \cdot \left(1 + 0.033 \cos \frac{360^\circ n}{365}\right) \cdot \left(cos\varphi cos\delta sin\omega_s + \frac{\pi \cdot \omega_s}{180} cos\varphi cos\delta\right) \quad (1)$$

$$\delta = 23.45 \cdot sin\left(360 \cdot \frac{284 + n}{365}\right) \quad (2)$$

$$\omega_s = cos^{-1}\left(-tan\varphi \cdot tan\delta\right) \quad (3)$$

where G_{sc}=1367 W/m^2 is the solar constant, n is the day of the year, and φ is the latitude of the location.

Around a specific region, solar radiation data are commonly measured at a limited number of measurement stations. Therefore, to accurately calculate solar radiation data, a comparison of several ML techniques was conducted, and then the technique that demonstrated the highest accuracy in predicting global solar radiation was selected and implemented for further optimization of the model. To develop a model for predicting the intensity of global solar radiation on a horizontal surface, meteorological parameters were recorded at the weather station located in Cacak, Serbia (latitude 43.89° N, longitude 20.35° E, elevation 240 m).

The research focused on a data collection period from March to July, renowned for intensive solar collector use, as it provides optimal conditions for solar energy utilization. The recorded data, including maximum and minimal air temperature, air humidity, daily sunshine duration, and global solar radiation on the horizontal surface, are used as inputs for the model development process. In addition, the mean horizontal daily extraterrestrial solar radiation is included as an input parameter for the model. The output data of the model are the measured values of the global solar radiation on the horizontal surface, which serve as the target values for prediction.

The daily measured values of the meteorological parameters used in the testing and training phase of the solar model are shown in Figures 2-5.

For modeling global radiation as a function of defined input variables, the following ML techniques were used.

A supervised ML technique SVM was developed to address both classification and regression issues. In regression tasks, the goal is to predict a continuous output variable, while classification tasks involve predicting discrete output variables (class labels). Unlike classification scenarios where accurate predictions are attainable, regression predictions cannot be exact, due to the real-valued nature of the output. Consequently, an error term is introduced, and a loss function ε is established to calculate errors within a certain margin of the true value (Vapnik, Golowich & Smola, 1997). In this study, various kernel functions of SVM (Rodríguez-Pérez & Bajorath, 2022) are applied (Linear, Quadratic, Cubic and Gaussian) and the best performance was obtained for Cubic kernel function (with RMSE=341.5, R^2=0.98 and 10% hold-out validation, as it can be seen in Figure 6(a)).

The decision tree is a non-parametric supervised learning technique used for classification and regression tasks in data mining. It represents data using tree structures with nodes dividing the data based on if-then scenarios. Recursive tree-building algorithms progressively split the training data into subsets, creating a comprehensive structure (Breiman et al., 1984; Jung, 2022). Figure 6(b) shows the comparison between the predicted and the measured values of the medium tree model of global solar radiation on a horizontal surface (with RMSE=502.92, R^2=0.95 and 10% hold-out validation).

GPR is a nonparametric, Bayesian technique for regression that has gained popularity in ML. The probability distribution for each valid function that can fit the data is calculated by GPR. Although a prior (on the function space) is supplied, the

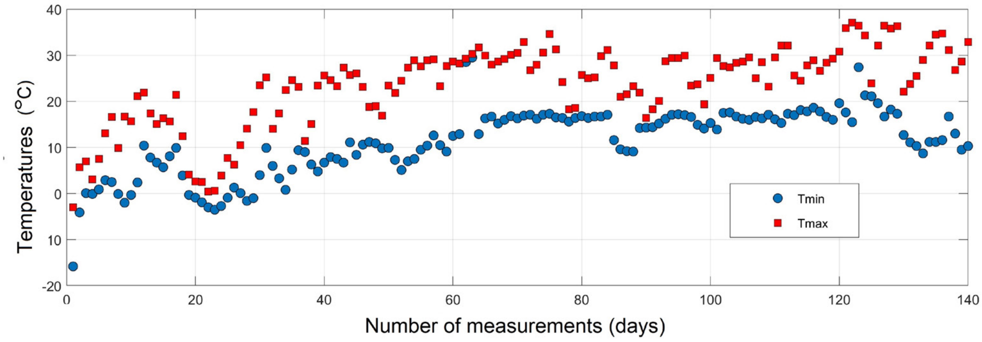


Figure 2. Minimum (T_{min}) and maximum (T_{max}) air temperatures

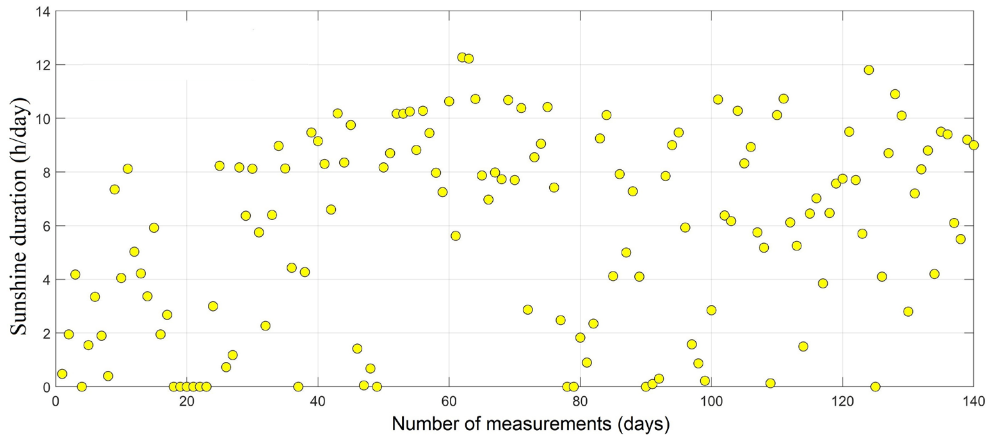


Figure 3. Sunshine duration

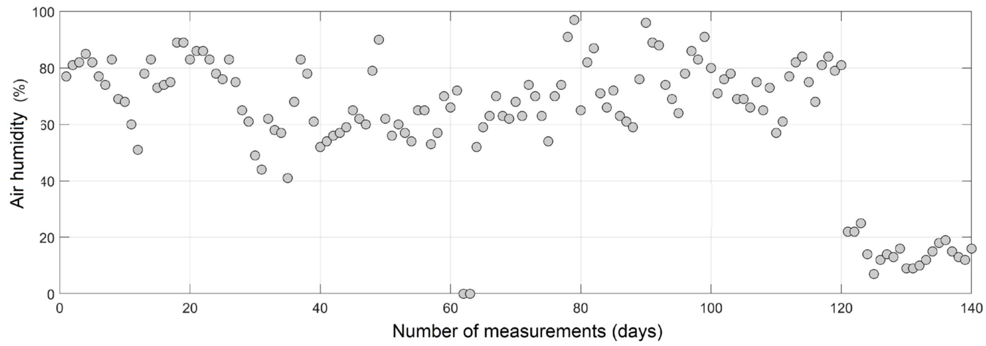


Figure 4. Average relative humidity

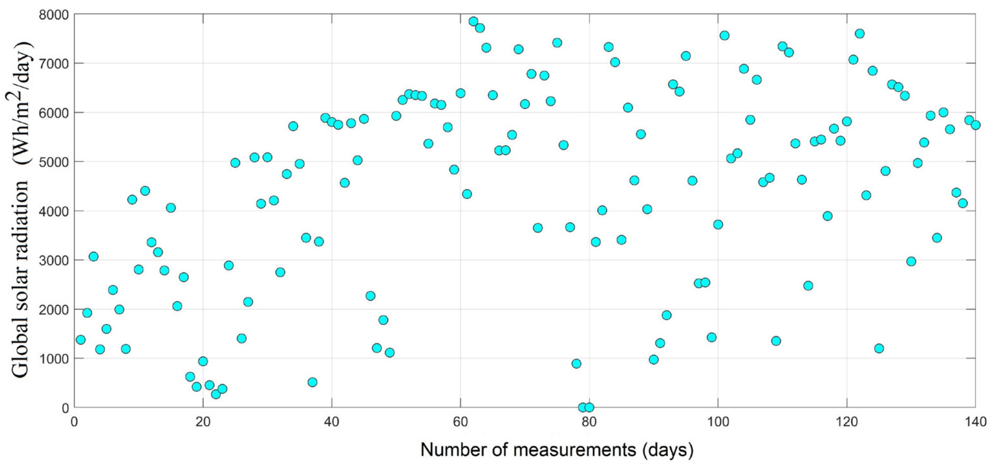
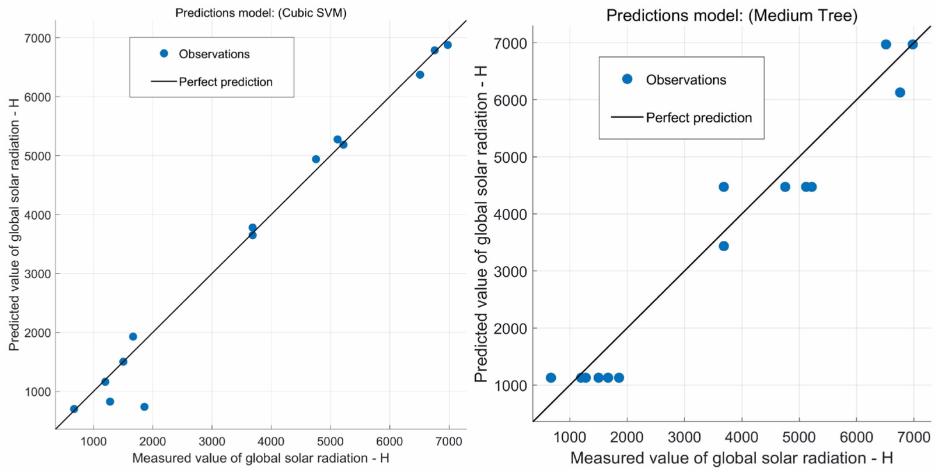


Figure 5. Global solar radiation on a horizontal surface

posterior is computed using the training data, and the predicted posterior distribution is computed on the points of interest of the present paper, these steps are similar to those described above. GPR has a number of advantages, including the ability to provide uncertainty measurements for the predictions and a proper functioning on tiny datasets (Rasmussen & Williams, 2006; Spong, Hutchinson & Vidyasagar, 2006). Figure 7(a) shows the obtained results for exponential GPR (with RMSE=164.37, R^2=0.99 and 10% hold-out validation).

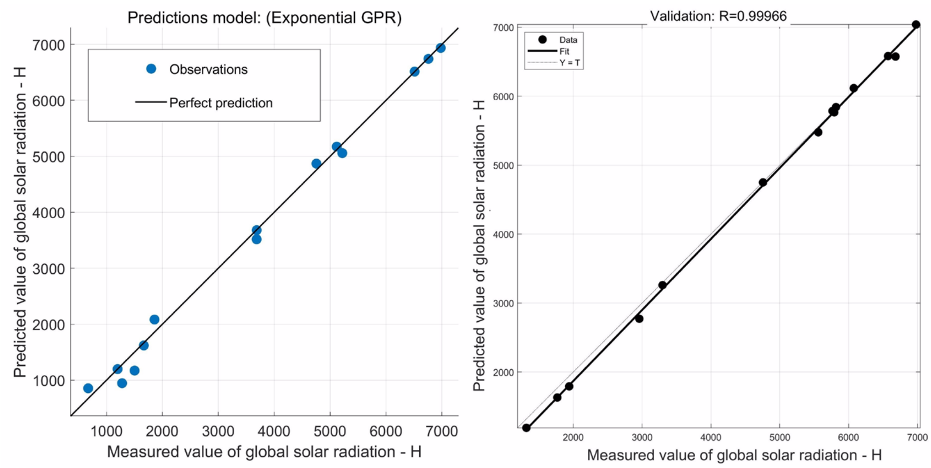
ANN represents a methodology by which knowledge gathered from data sets is placed in a distributed form into a connected network structure. ANN consists of simple interconnected processing units, neurons. An improved version of the basic backpropagation algorithm, the Levenberg-Marquardt algorithm, is used for training. The Levenberg-Marquardt algorithm is a numerical optimization technique that is very successfully applied in the training of multilayer perceptrons and ensures fast and stable convergence (Hagan & Menhaj, 1994). The total number of performed experiments is 140. The dataset is arbitrarily divided into training, validation and testing sets (80%, 10%, and 10%, respectively). The training of the ANN ends in the 29th iteration, the RMSE performance in the case of the presented ANN model is 92.39, and R^2=0.999 (see Figure 7(b)).

After comparing the performances of four ML techniques, the ANN model has been chosen for investigating the optimal tilt angle of the solar panel, due to its highest accuracy in predicting global solar radiation.



(a) (b)

Figure 6. The predicted vs. measured global solar radiation
a) SVM model; b) The decision tree model



(a) (b)

Figure 7. The predicted vs. measured global solar radiation
a) GPR model; b) ANN model

4. Genetic Algorithm Optimization of Solar Collector Tilt Angle

4.1 Mathematical Modeling

By harnessing the power of cutting-edge neural network models, the efficiency of solar energy systems can be enhanced. One such application involves utilizing predicted values of global solar radiation on a horizontal surface as an input parameter to determine the optimal angle of inclination for solar collectors. This approach enables maximizing the absorption of solar radiation on tilted surfaces and optimizing energy generation.

For the calculation of solar potential of inclined surfaces, it is essential to consider all components of solar radiation. Using the isotropic model, the solar radiation on a tilted surface can be calculated from (Duffie & Beckman, 2013):

$$H_t = H_b R_b + H_d\left(1+cos\beta\right)/2) + H\rho_g\left(1-cos\beta\right)/2) \quad (4)$$

where R_b is the geometric factor, β is the tilt angle, and ρ_g is the ground reflectance factor. In equation (4), the first term represents direct solar radiation emitted by the sun, the second term represents diffuse radiation, and the last term represents radiation reflected by the ground in front of the collector.

The geometric factor indicates the direct radiation on the tilted surface in relation to the direct radiation on a horizontal surface at any given time. The following equation defines the geometric factor for a surface in the Northern Hemisphere pointing directly toward the equator (Duffie & Beckman, 2013):

$$R_b = \frac{\cos\left(f-\beta\right)\cos\delta\cos w_s^{'} + \left(p/180\right)w_s^{'}\sin\left(f-\beta\right)\sin\delta}{\cos\varphi\cos\delta\cos w_s + \left(p/180\right)w_s\sin f\sin\delta} \quad (5)$$

where $w_s^{'}$ is the sunset hour angle of the tilted surface, which is determined by:

$$w_s^{'} = min\begin{bmatrix} cos^{-1}\left(-tan\phi\ tan\delta\right) \\ cos^{-1}\left(-tan\left(\phi-\beta\right)\ tan\delta\right)\end{bmatrix} \quad (6)$$

Beam and diffuse radiation are two distinct components of solar radiation, and solar energy systems utilize them in different ways to optimize energy generation. The tilt angle of solar collectors is crucial for optimizing the utilization of both beam and diffuse radiation. To calculate both beam and diffuse radiation, it is necessary to determine the clearness index, which is the ratio of the global solar radiation falling on a horizontal surface to the corresponding extraterrestrial radiation:

$$K_T = H/H_o \quad (7)$$

The diffuse components can be approximated using the following set of correlations (Duffie & Beckman, 2013):

For $\omega_s \leq 81.4°$:

$$\frac{H_d}{H} = \begin{cases} 1-0.2727K_t+2.4495K_t^2-11.951K_t^3+9.3879K_t^4 & K_t<0.715 \\ 0.143 & K_t \geq 0.715 \end{cases} \quad (8)$$

for $\omega_s > 81.4°$:

$$\frac{H_d}{H} = \begin{cases} 1+0.2832K_t-2.5557K_t^2+0.8448K_t^3 & K_t<0.722 \\ 0.175 & K_t \geq 0.722 \end{cases} \quad (9)$$

The beam component of solar radiation of horizontal surface is calculated using the following equation:

$$H_b = H - H_d \quad (10)$$

4.2 GA Optimization

The literature references (Holland, 1992; De Jong, 1985) have extensively discussed and studied a family of GAs adaptive search algorithms. The fact that GAs are loosely based on models of genetic change in a population of individuals gives them their name. These models comprise three essential components: a Darwinian concept of fitness which determines the extent to which an individual can influence subsequent generations; a mating operator that creates progeny for the next generation; and genetic operators which determine the genetic makeup of offspring based on the genetic material inherited from their parents (De Jong, 1988; Goldberg, 2008).

In GA optimization for solar energy systems, a crucial step involves determining the fitness function, which encapsulates specific criteria and objectives to be optimized, with the goal of maximizing the desired outcome, such as optimizing tilt angle. In this case of maximizing solar radiation on a tilted surface, H_t which is the fitness function given by equation (4), is designed to assess and assign a fitness value based on the achieved H_t value. Therefore, the goal of optimization is to find the β angle for which the radiation H_t has the maximum value. The search range for the β angle between 0 to 90 degrees was considered, encompassing the full spectrum of possible angles.

The 50 individuals make up the population, with a maximum of 100 generations. The choice is made using the roulette algorithm. The population is represented as a map on a roulette wheel, with higher fitness strings taking up more space on the wheel. The roulette has N points uniformly distributed on it, where N is the total number of individuals in a population. The roulette is spun once, creating a population. The operator of the crossing utilises a uniform crossover. The “crossover percent” has a value of 0.8. The crossover fraction (0-1) describes the non-elite members of the new population that results from a crossing. Only five great individuals may be passed on to the following generation.

The working principle of the GA is exemplified for a specific location (latitude 43°89’ N), a particular day of the year (day 68), and recorded weather parameters (T_{min}=-2°C, T_{max}=16.7°C, sunshine duration of 7.35 hours, average humidity 69 %). After processing these input data, the variables of the fitness function yielded the following values:

$$H = 9.45\left(\text{ANN prediction}\right); H_b = 2.19;$$

$$R_b = 1.52; H_d = 7.26; \rho = 0.4.$$

Therefore, the fitness function can be expressed as follows:

$$H_t = 3.33 + 7.26 \cdot \frac{1+\cos\beta}{2} + 3.78 \cdot (1-\cos\beta)/2 \quad (11)$$

The optimization process stopped after 51 iterations (generation), and the maximized value of solar radiation is H_t =10.29 MJ/m^2. The result of the optimization process for the selected day indicates that the optimal tilt angle is β=34.57° (Figure 8).

According to the presented principle, the optimization of the tilt angle of the collector was performed for each day of the month of March. Figure 9 shows the daily average solar radiation received by the solar collector at different tilt angles, providing a comprehensive overview of the variations throughout the month.

Figure 9 illustrates the considerable impact of the tilt angle on solar radiation, showing that, as the inclination angle deviates from horizontal to a specific value, the incident solar energy radiation on the flat surface noticeably increases. The daily distribution of solar radiation indicates that optimal angles change from 0° to 53.2° in order to ensure that the solar collector receives the highest

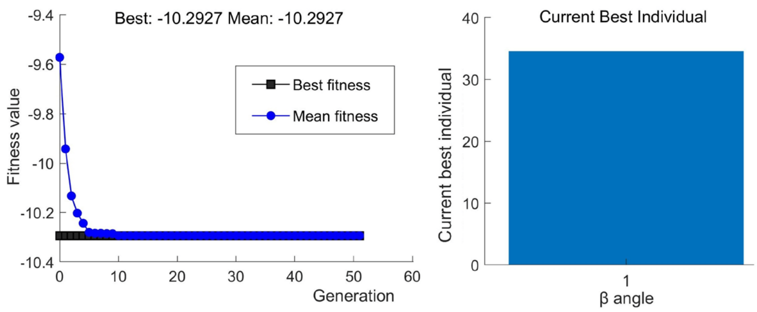


Figure 8. GA optimization process and optimal tilt angle

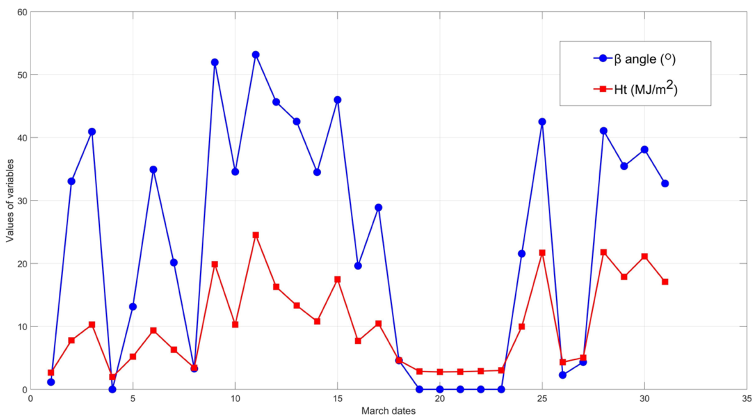


Figure 9. Daily solar energy variation with tilt angles for selected month – March

radiation levels. The results further demonstrate that on March 11, the maximum daily radiation recorded was 24.54 MJ/m^2, while the minimum value of 1.96 MJ/m^2 occurred on March 4. These findings highlight the crucial importance of selecting the appropriate tilt angle to maximize solar radiation and subsequent energy generation.

The analysis in Figure 9 shows that the optimal tilt angle increases with higher radiation rates, particularly on clear days compared to cloudy ones. The variation in the clearness index throughout March (0.11-0.69) influenced by the position of the sun, turbidity, and cloud cover, affects the optimal tilt angle, which remains relatively constant within a small range from 45.7° to 53.2° on clear days, reflecting the dominance of direct solar radiation. These findings underscore the importance of considering weather conditions in optimizing solar energy systems for increased energy generation.

Conversely, low clearness index values are associated with low global radiation, typically occurring on cloudy days with a significant portion of diffuse radiation. The diffuse component has a notable impact on the optimal tilt angle, leading to a wide range of optimal tilt angles for the solar collector during the 21 cloudy days, varying from 0° to 42.60°. In the presence of a high diffuse fraction, it is optimal for the solar collector to have a larger sky-facing area and a lower tilt angle to capture a greater proportion of diffuse radiation. Clouds obstruct the direct component of solar radiation, making the diffuse component more significant in these conditions.

The results indicate that varying weather conditions, which can significantly differ from day to day and exhibit pronounced variations throughout the year, have a substantial impact on the optimal tilt angle values. The presented AI-based approach offers an automated solution for determining the optimal tilt angle, considering the intricate interplay of weather conditions and maximizing energy capture efficiently.

Due to the unpredictability of meteorological and geographic parameters, many researchers came to the conclusion that the optimal inclination of a solar collector is particularly site-specific and must be carefully investigated, taking into account long-term observational datasets (Obiwulu et al., 2022; Raptis et al., 2017). An effective technique to gather the most energy each day is to employ a tracking system, which is still regarded as expensive. Because of this, non-computational ways to estimate the optimal tilt angle for any latitude have been offered in the literature. The simple relation $\beta = \varphi - \delta$ is proposed by Duffie and Beckman (2013), where the optimal tilt angle for a flat plate collector should be calculated using only functions of the latitude and declination. The computed solar radiation incident on an optimally inclined surface using the given relation and the proposed AI-based methodology varies up to 4.5 %. In terms of its practical application, the developed model provides higher solar global radiation on an inclined surface, which increases the efficiency of solar energy transformation. Also, unlike numerous theoretical models, the presented model takes into account real meteorological conditions that significantly affect the optimal tilt angle and the amount of energy that reaches the solar collector.

5. Conclusion

In this research, a novel approach combining different ML techniques is proposed to optimize the utilization of solar energy. Different ML models were developed to predict the daily average global solar radiation on a horizontal surface, using meteorological data obtained from a weather station for training and testing the models. The results show that the ANN model outperformed other models in predicting global solar radiation, demonstrating high accuracy in estimating the daily average global solar radiation. Additionally, the study focuses on optimizing the tilt angle of a solar collector to achieve maximum daily solar radiation. This optimization process has employed a GA and utilized the best predicted values of global solar radiation obtained through the ANN model. The results demonstrated that the optimal tilt angles for daily solar radiation distribution varied within the range 0° to 53.2° in March.

An advantage of this hybrid model is its ability to accurately predict daily solar radiation data and calculate the optimal tilt angle of a solar collector, using readily available weather forecasting data.

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REFERENCES

Breiman, L., Friedman, J. H. & Olshen, R. A. (1984) *Classification and Regression Trees*. California, USA, Wadsworth International Group, Pacific Grove.

Datta, S., Bhattacharya, S. & Roy, P. (2016) Artificial Intelligence based Solar Panel Tilt Angle Optimization and its Hardware Implementation for Efficiency Enhancement. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*. 5, 7830-7843. doi: 10.15662/IJAREEIE.2016.0510006.

De Jong, K. (1985) Genetic algorithms: A 10 year perspective. In: *Proceedings of the First International Conference on Genetic Algorithms and Their Applications, 24-26 July 1985, Carnegie-Mellon University, Pittsburg, PA*. New Jersey, United States, Lawrence Erlbaum Associates. pp. 169-177. doi: 10.5555/645511.657077.

De Jong, K. (1988) Learning with genetic algorithms: An overview. *Machine Learning*. 3, 121-138. doi: 10.1023/A:1022606120092.

Dučić, N., Jovičić, A., Manasijević, S., Radiša, R., Ćojbašić, Ž. & Savković B. (2020) Application of Machine Learning in the Control of Metal Melting Production Process. *Applied Sciences*. 10(17), 6048. doi: 10.3390/app10176048.

Duffie, J. A. & Beckman, W. A. (2013) *Solar Engineering of Thermal Processes.* New York, USA, John Wiley and Sons Inc. doi: 10.1002/9781118671603.

Goldberg, E. D. (2008) *Genetic Algorithms in Search, Optimization and Machine Learning*. Upper Saddle Rive, India, Pearson Education India.

Hagan, T. M. & Menhaj, M. B. (1994) Training feed-forward networks with the Marquardt algorithm. *IEEE Transactions on Neural Netwoks.* 5, 989-993. doi: 10.1109/72.329697.

Holland, J. H. (1992) *Adaptation in Natural and Artificial Systems*. Cambridge, Massachusetts, USA, MIT Press.

Jung, A. (2022) *Machine Learning: The Basics*. Part of the book series: Machine Learning: Foundations, Methodologies, and Applications. Dordrecht, Heidelberg, London, New York, Springer.

Kim, G. Y., Han, D. S. & Lee, Z. (2020) Solar Panel Tilt Angle Optimization Using Machine Learning Model: A Case Study of Daegu City, South Korea. *Energies.* 13(3), 1-13. doi: 10.3390/en13030529.

Kulkarni, S., Duraphe, K., Chandwani, L., Jaiswal, S., Kakade, S. & Kulkarni, R. (2021) Optimizing Solar Panel Tilt Using Machine Learning Techniques. In: *3rd Global Power, Energy and Communication Conference (GPECOM), 5-8 October 2021, Antalya, Turkey*. New Jersey, USA, Institute of Electrical and Electronics Engineers (IEEE). pp. 190-195. doi: 10.1109/GPECOM52585.2021.9587892.

Lima, M. A. F. B., Fernadez-Ramirez, L. M., Carvalho, P. C. M. & Freitas, D. M. (2021) A Comparison Between Deep Learning and Support Vector Regression Techniques Applied to Solar Forecast in Spain. *Journal of Solar Energy Engineering*. 144, 010802. doi: 10.1115/1.4051949.

Mellit, A. & Kalogirou, S. (2022) *Handbook of Artificial Intelligence Techniques in Photovoltaic Systems: Modeling, Control, Optimization, Forecasting and Fault Diagnosis*. Cambridge, Massachusetts, USA, Academic Press.

Narvaez, G., Giraldo, Luis. F., Bressan, M. & Pantoja, A. (2021) Machine learning for site-adaptation and solar radiation forecasting. *Renewable Energy*. 167, 333-342. doi: 10.1016/j.renene.2020.11.089.

Obiwulu, A. U., Erusiafe, N., Olopade, M. A. & Nwokolo, S. C. (2022) Modeling and estimation of the optimal tilt angle, maximum incident solar radiation, and global radiation index of the photovoltaic system. *Heliyon*. 8(6), e09598. doi: 10.1016/j.heliyon.2022.

Olatomiwa, L., Mekhilef, S., Shamshirband, S. & Petković, D. (2015) Adaptive neuro-fuzzy approach for solar radiation prediction in Nigeria. *Renewable and Sustainable Energy Reviews*. 51, 1784-1791. doi: 10.1016/j.rser.2015.05.068.

Pereira, S., Abreu, Edgar.F.M., Iakunin, M., Cavaco, A., Salgado, R. & Canhoto, P. (2022) Method for solar resource assessment using numerical weather prediction and artificial neural network models based on typical meteorological data: Application to the south of Portugal. *Solar Energy.* 236, 225-238. doi: 10.1016/j.solener.2022.03.003.

Quej, V. H., Almorox, J., Arnaldo, J. A. & Saito, L. (2017) ANFIS, SVM and ANN soft-computing techniques to estimate daily global solar radiation in a warm sub-humid environment. *Journal of Atmospheric and Solar-Terrestrial Physics*. 155, 62-70. doi: 10.1016/j.jastp.2017.02.002.

Raptis, I., Kazadzis, S., Psiloglou, B., Kouremeti, N., Kosmopoulos, P. & Kazantzidis, A. (2017) Measurements and model simulations of solar radiation at tilted planes, towards the maximization of energy capture. *Energy*. 130, 570-580. doi: 10.1016/j.energy.2017.04.122.

Rasmussen, C. E. & Williams, C. K. (2006) *Gaussian Processes for Machine Learning*. Cambridge, USA, Massachusetts Institute of Technology, MIT-Press.

Rodríguez-Pérez, R. & Bajorath, J. (2022) Evolution of Support Vector Machine and Regression Modeling in Chemoinformatics and Drug Discovery. *Journal of Computer-Aided Molecular Design*. 36, 355-362, doi: 10.1007/s10822-022-00442-9.

Spong, M. W., Hutchinson, S. & Vidyasagar, M. (2006) *Robot Dynamics and Control*. John Wiley and Sons Inc., New York, USA.

Vapnik, V., Golowich, S. E. & Smola, A. J. (1997) Support vector method for function approximation, regression estimation and signal processing. *Advances in Neural Information Processing Systems*. 9, 281-287.

Yassir, A. (2019) Genetic Algorithm as a Solutions Optimization of Tilt Angles for Monthly Periods of Photovoltaic Installation. In: *International Conference on Science and Innovated Engineering (I-COSINE), 21–22 October 2018, Aceh, Indonesia.* IOP Conference Series: Materials Science and Engineering. 536(1), 012100. Birstol, UK, IOP Publishing. doi: 10.1088/1757-899X/536/1/012100.