INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

# Artificial Intelligence Applications in Solar Energy

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***Abstract*—Renewable energy research has become significant in the modern period due to escalating fossil fuel prices and the pressing need to reduce greenhouse gas emissions. Solar energy stands out among these sources due to its abundance and global accessibility. However, its weather-dependent and cyclical nature adds inherent risks, making effective planning and management difficult. Soft computing technologies provide attractive solutions for modeling such systems, while machine learning and optimization techniques are gaining popularity in the solar energy industry. The current literature highlights the growing use of soft computing technologies, emphasizing their potential to address difficult challenges in solar energy systems. To effectively reap the benefits, these strategies must be seamlessly connected with emerging technologies like the Internet of Things (IoT), big data analytics, and cloud computing. This integration provides a unique opportunity to improve solar energy systems' scalability, flexibility, and efficiency. Researchers can use these synergies to create intelligent, linked solar energy ecosystems capable of real-time optimization of energy production, delivery, and consumption. These technologies have the potential to transform the renewable energy environment, allowing for more resilient and sustainable energy infrastructures. Furthermore, as these technologies improve, there is a growing demand for trained experts to address associated cybersecurity problems, assuring the integrity and security of these sophisticated systems. The urgency and importance of interdisciplinary collaboration in this field cannot be overstated. Researchers may pave the road for a more sustainable and energy-efficient future by working collaboratively and using interdisciplinary methodologies.**

***Keywords*— Solar energy; machine learning; soft computing; neural networks; genetic algorithm.**

*Manuscript received 15 Dec. 2023; revised 19 Mar. 2024; accepted 12 Apr. 2024. Date of publication 31 May 2024.*


## I. INTRODUCTION

The present scenario of escalating fuel prices, greenhouse gas emissions, and changing geo-political conditions are driving the research toward renewable energy sources [1]–[4]. The researchers are investigating energy sources like tidal [5], [6], wave and ocean [7]–[9], biomass [10], [11], biofuels with some typical types, such as biodiesel [12]–[14], alcohol [15]–[19], furan [20]–[22], ether [23]–[25], natural gas [26]–[28]), wind [29]–[31], solar [32]–[34], and several other energy sources.

Solar energy is derived from solar irradiance, which might be thermal energy, a chemical transformation or process, or even clean electrical energy [35], [36]. The total quantity of solar energy that strikes the planet exceeds its present and future demands; therefore, if properly harnessed, this highly distributed source might supply all of our energy needs [37], [38]. Solar energy, unlike typical forms of energy like coal, petroleum, and natural gas, has lately emerged as one of the most widely used and ecologically safe energy sources, implying that it will endure millions, if not billions, of years. The sun is more than simply a powerful energy source; it is by far the most plentiful source of energy the planet acquires. However, its strength at the surface is relatively low, mainly owing to the distance between the Earth and the sun, which causes a wide radial dispersion of energy along the route [39]–[41]. The atmosphere of the earth and clouds absorb or disperse over half of the sunlight that enters, resulting in a minor additional loss. More than half the amount of sunlight from the sun is visible light, while the remainder comprises infrared, ultraviolet, and other types of electromagnetic radiation. The quantity of raw energy obtained from the sun is sufficient to meet the planet's energy demands hundreds of times because solar energy has an insurmountable potential that must be fully explored [42]–[44]. Unfortunately, notwithstanding having been proven that solar energy is free and available practically everywhere, the high cost of gathering, converting, and storing it limits its utilization in many areas worldwide. Solar radiation may be converted into thermal energy or electrical energy. However, the former type is more accessible since the heat released by the sun can be applied immediately for heating for an extended period [45]–[47]. Sun-derived solar energy is growing in popularity due to its adaptability in various industrial uses [48], [49]. These applications include the production of electricity for domestic and commercial usage [49]–[51], freshwater production [52]–[54], the sun drying of fruits for food industry processing [55]–[57], hydrogen production [58]–[60], and heat production [61]–[63].

In addition, organizations and governments are supporting the utilization of renewable energy and solar energy via a variety of laws and incentives because it is relatively safe to use, can be scaled up, and has a positive influence on the environment in comparison to other sources [64]–[68], this shifting progress to renewable energy could be observed for the post-COVID19 pandemic [69], [70]. The present installed generation capacity for solar energy may be larger than that of wind energy; nevertheless, it is anticipated that solar power will have a growth rate of 47.6% on an annual basis, while wind energy has been projected to have a growth rate of 18.9% [71]. Recent years have seen significant advancements in solar power, notably in the field of photovoltaic (PV) technology, in which solar energy could be integrated into energy production along with other sources such as coal, biomass, wind, and geothermal [72]–[74]. The manufacture of perovskite solar cells has the promise of increased efficiency as well as decreased manufacturing costs, which has the possibility of completely transforming the market [75]–[78]. Building-integrated photovoltaics, which is an expansion of solar technology that incorporates solar energy tracking systems and the incorporation of solar activity into construction supplies, has increased the usefulness of solar technology while also improving its aesthetics [79], [80]. On a bigger scale, concentrated solar power facilities are reaping the benefits of increased thermal storage capacities. These capabilities enable resource dispatch ability regardless of whether the sun is shining [81], [82]. A brief comparison of solar-based power systems is depicted in Fig. 1 [83].

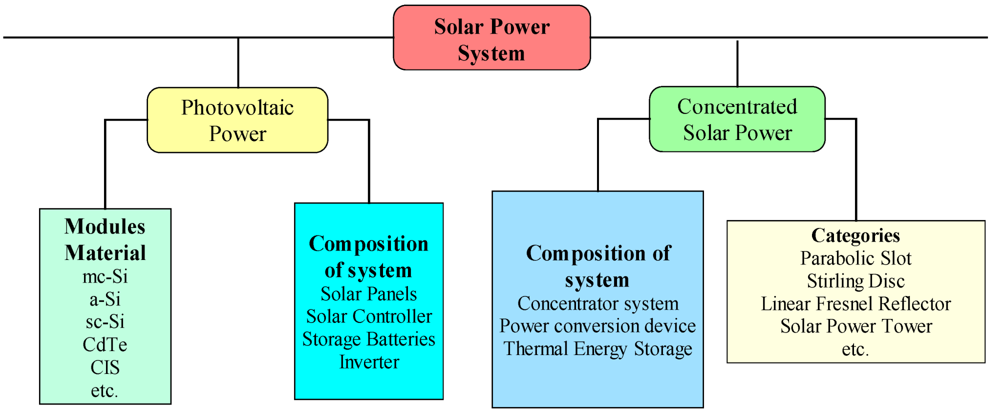


Fig. 1 Solar power system [83]

Soft computing is a subfield of Artificial intelligence (AI) that includes several approaches for handling complex and non-linear real-life problems [84], [85]. Unlike traditional computing methods, which depend on specific mathematical functions and algorithms [34], [86], [87]. Soft computing techniques simulate human-like reasoning and selection-making procedures [88], [89]. These methods are particularly useful for dealing with demanding situations consisting of ambiguity, imprecision, and inadequate data [90][91]. Thus, it renders them crucial in plenty of sectors of manufacturing, finance, engineering, healthcare, and environmental studies [92]–[94]. Several principal approaches underpin soft computing, like genetic algorithms (GA), ANN, fuzzy logic, support vector machines (SVM), and evolutionary algorithms. These techniques reflect human cognitive strategies and use historical data to make educated judgments [95]–[98]. For example, artificial neural networks are stimulated by the human brain's shape and features, which include linked nodes (neurons) that procedure and examine information. ANNs can identify patterns, categorize information, and forecast with exquisite accuracy after being trained [99]–[101]. A brief classification of soft computing is depicted in Fig. 2 [102].

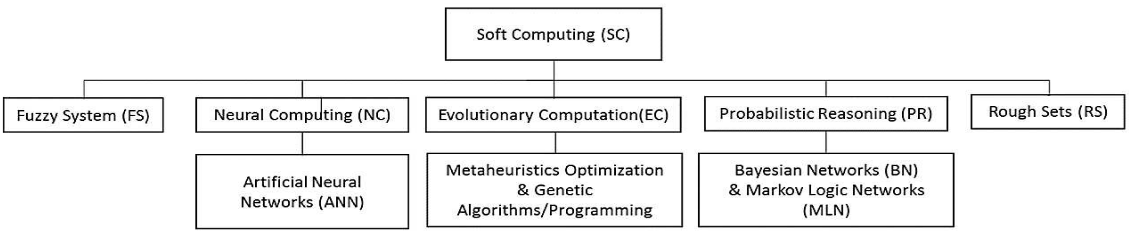


Fig. 2 Main soft computing methods [102]

Fuzzy logic is one of the crucial ML approaches in soft computing. The adaptability of fuzzy logic makes it ideal for applications requiring linguistic variables and fuzzy sets, which include temperature manage systems, choice-making tactics, and professional systems [103], [104]. Genetics and evolutionary approaches are heavily influenced by biological evolution and natural selection theory. These optimization methods entail generating and developing a desired solution to the problem throughout multiple generations. Mutation, cross-over, selection, and other genetic algorithms are commonly used for candidates in difficult regions, preferred solutions or closest approach assertions, genetics, and algorithms [105]–[108]. Fig. 3 depicts a typical application framework of soft computing in the solar energy domain [109].

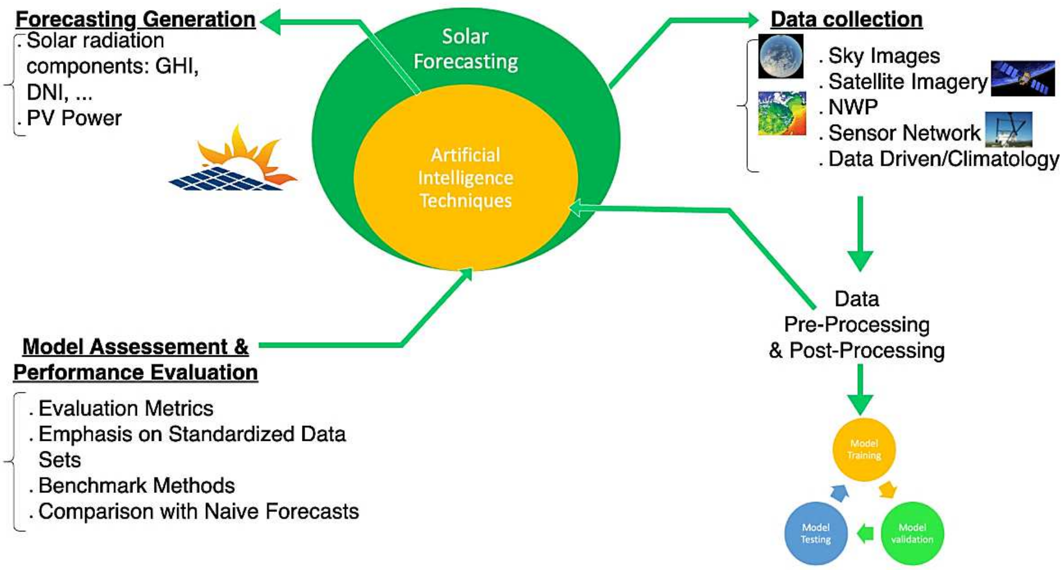


Fig. 3 Application framework of soft computing in solar energy [109]

Support vector machines (SVMs) are highly effective supervised learning models for classification and regression problems. SVMs work by feeding input data into a high-dimensional feature space and identifying the optimum hyperplanes separating classes or showing continuous results by maximizing margins between classes; kernel functions have been employed to manage nonlinear relationships [110]–[112]. SVMs may effectively categorize complex data and generalize previously unseen data. In the context of solar energy uses, soft computing plays a vital part in harvesting, converting, and using solar energy. A simple computer model can precisely predict solar radiation and maximize the efficiency of the solar power system [113], [114].

## II. Material and Method

### A. Artificial Neural Networks

The artificial neural network, also known as an ANN, is a simplified form of biological-based neural architecture that is capable of effectively correlating a greater number of uncertain input points to a variety of characteristics [115]–[117]. There is no need for mathematical equations or a sophisticated mathematical base when it comes to the process of building relationships between various factors [118], [119]. ANN models use such an approach. Consequently, when trying to link the 'n' number of control factors with several numbers of indeterminate data values, ANN needs less processing effort than traditional techniques. This is because ANNs can learn from their data [120]–[122].

The process of training the ANN by making use of data that has been imported is referred to as supervised training or learning. Similar to neurons that are found inside a human brain, the ANN is made up of a number of neurons. The weight of these neurons is a fractional number that represents their connection to one another [123], [124]. These neurons are related to one another by this weight. It is necessary to make adjustments to the weights throughout the training process to provide accurate predictions of the outcomes. Once the error has reached a level that is considered acceptable, the weight values will remain constant [125]–[127].

It is shown in Fig. 4 that the fundamental structure of the ANN comprises three levels: the input layer, the hidden layer, and the output layer. Each of these layers is composed of neurons [128]. Whereas the selection of input parameters determines the number of neurons in the input layer, the selection of output parameters determines the number of neurons in the output layer [129], [130]. In other words, the neurons in the output layer are controlled by the output parameters. To determine the total number of neurons that are concealed, the trial-and-error approach is used in a variety of contexts. The bias is an additional parameter that is used to change the output of the neural network according to the requirements of the situation, the symbol 't' represents the passage of time [131]–[133].

The whole data set of control factors-response variables is divided into two groups: the first group, which contains a more significant chunk of data points, is referred to as the training data set, and it is used to train the neural network [134]–[136]. The second group, which contains the remaining data points, is utilized to verify the trained neural network. Using a neural network, the input-output parameters and training data points are loaded [137], [138]. This network is trained until it reaches an error level that is considered acceptable. After defining the degree of error that is considered sufficient, the trained network is validated by importing the values of the input parameters from the validation data set and predicting the values of the output parameters that correspond to those values [139], [140]. These predicted values of the test data set's output parameter are contrasted to the corresponding actual values of the validation data set's output parameter. If the variance across the real and anticipated outcomes is less than the permissible limit, the trained neural network may be recommended as the ideal neural network for the prediction. This conclusion is reached if the error is less than the allowable limit. A typical architecture of ANN is depicted in Fig. 4 [128], [141].

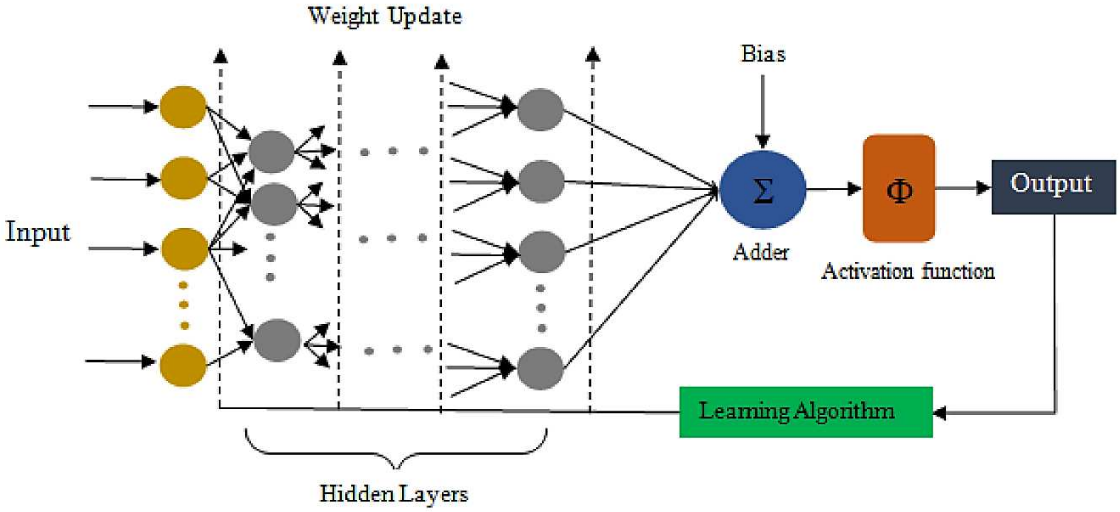


Fig. 4 ANN architecture [128]

During the process of training a neural network, several different training algorithms are used. The training function, the learning variant, the transfer function, and the number of hidden neurons are all taken into consideration by these respective approaches [142]. For the purpose of training, there are a number of different transfer functions, learning versions, and training functions that may be used [143]. The training is carried out for the period specified in the requirements. To choose the appropriate training technique and training epochs, a neural network will take into account the values of the input parameter and then make predictions about the values of the output parameter based on those predictions [144], [145]. In the event that the error value is lower than the permissible value, the trained neural network that employs that particular combination of training algorithms has the possibility of being selected as the ideal neural network with the most effective training algorithm. For training the NN, the same technique is followed, but the number of epochs or the training algorithm that is used may vary [146], [147]. This process continues until the maximum allowable error is achieved. For the purpose of providing a greater error value, this is done. The generalization of the training neural network is validated by the outcomes that are anticipated by the ideal neural network, which are based on validation data points [148]–[150].

*B. Fuzzy Logic*

The usage of fuzzy logic, which is often linked primarily to rule-based systems including expert systems, is in fact capable of being utilized as a regressor in machine learning. In specific circumstances, fuzzy logic has several distinct advantages, despite the fact that it may not be utilized for regression jobs as frequently as other methods, such as linear regression or neural networks [103], [151], [152]. When modeling the correlation between input and output variables, fuzzy logic-based regression makes use of fuzzy rules as well as membership functions rather than exact mathematical formulae. This allows for a more accurate representation of the relationship [153], [154]. The modeling of complicated, non-linear connections that may be difficult to quantify using typical regression approaches is made possible by these rules, which capture the linguistic linkages that exist between the characteristics that are input and the result that is desired [155]. A flow chart for fuzzy logic is depicted in Fig. 5 [156].

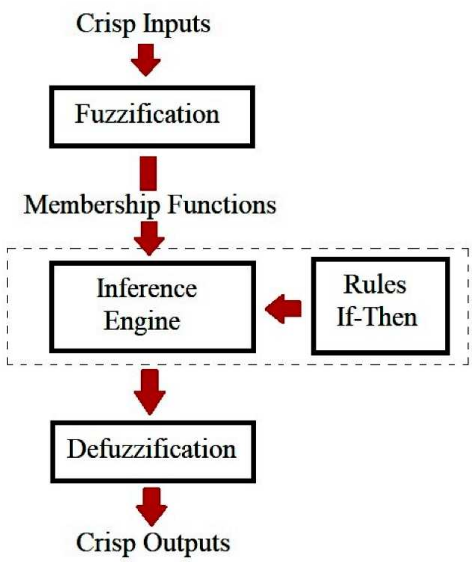


Fig. 5 Flow chart of fuzzy logic [156]

The following are the stages that are involved in the procedure of fuzzy logic regression [103], [157]:

*1) Fuzzification*: Converting crisp input values into fuzzy sets by utilizing membership functions is the first step in the fuzzification process. These membership functions are used to express the extent to which a given input value is associated with each possible fuzzy set [158].

*2) Rule Evaluation*: Applying fuzzy logic laws to the fuzzy inputs to assess the degree of activation of each rule is the second step in the regulation evaluation process. Input variables are defined by these rules, which specify how they interact to generate an output [159].

*3) Inference*: Combine the rules that have been activated to produce a fuzzy output by utilizing fuzzy inference methods such as Mamdani or Sugeno [160].

*4) Defuzzification*: Reconvert the fuzzy output into a crisp output value by employing defuzzification techniques such as the centroid or the weighted average [161].

Fuzzy logic regression may be especially helpful in circumstances in which the link between the variables that are input and those that are output is not well defined or in which the data is intrinsically uncertain or imprecise [162], [163]. Fuzzy logic regression, for instance, can be a flexible and interpretable method of modeling that can be utilized in applications such as climate modeling, economic forecasting, or medical diagnosis, all of which involve inputs that may be qualitative or uncertain [164], [165]. It is essential to remember that fuzzy logic regression might only sometimes be the most suitable option for every single regression problem. It may have difficulty with datasets that are extremely vast or high-dimensional, and its success may be largely dependent on the design of the fuzzy rules and membership functions, which can be subjective and need knowledge in the relevant domain [166]–[168].

Generally speaking, fuzzy logic regression might not be as extensively utilized as other regression approaches, yet it provides a distinctive method for modeling complicated connections and dealing with uncertainty, which makes it a handy instrument in some machine learning applications.

### *C. Support Vector Machines*

Support Vector Machines, commonly known as SVMs, are well acknowledged for their effectiveness in classification tasks; nevertheless, they may also be employed as regressors. When it comes to dealing with non-linear and high-dimensional data, Support Vector Machine (SVM) regression, which is additionally referred to as Support Vector Regression (SVR), can be especially useful [169]–[171]. SVM regression is a technique that is very similar to SVM classification in that the goal is to locate the hyperplane that provides the most incredible fit to the data points while simultaneously maximizing the margin. Regression, on the other hand, seeks to reduce the departure or inaccuracy of the data points relative to the hyperplane rather than precisely splitting them into classes [172]–[174]. This is contrary to the purpose of classification using regression. The flow chart of SVM applied to solar energy is depicted in Fig. 6 [175].

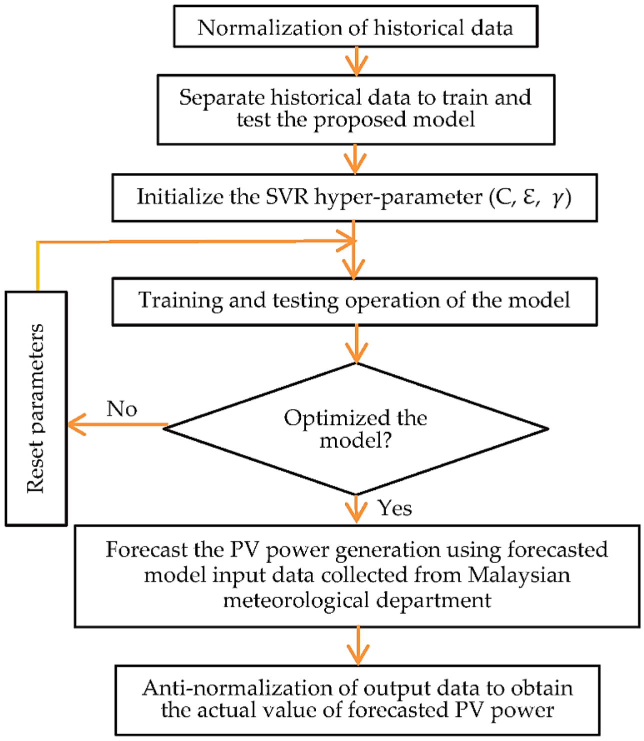


Fig. 6 SVM framework for solar energy prediction [175]

The following are the steps that are involved in the process of SVM regression:

*1) Kernel Selection*: To translate the input data into a higher-dimensional space, selecting an appropriate kernel function is necessary. Some examples of kernel functions are linear, polynomial, and radial basis functions (RBF) [176], [177].

*2) Training of model:* During model training, locate the hyperplane (decision boundary) that provides the best fit to the training data while using the least amount of error possible. By finding a solution to the optimization issue that was defined within the SVR framework, this may be accomplished [178].

*3) Evaluation*: Using data from validation or cross-validation techniques, evaluate the performance of the trained SVR model before moving on to the next step, model evaluation. The mean squared error (MSE), the mean absolute error (MAE), and the coefficient of determination ($R^2$) are all examples of standard metrics used in assessment [179].

*4) Prediction*: You should use the taught SVR model to generate predictions on fresh data points you have not seen before. The continuous output variable is represented by the values that were expected [180].

SVM regression provides some benefits in comparison to more conventional regression methods. It is resistant to overfitting because of the margin parameter, which regulates the balance between the complexity of the model and its ability to generalize about the data [181]. In addition, support vector machines can successfully manage high-dimensional data and non-linear correlations between input and output variables, making them suited for various regression problems [182], [183]. On the other hand, SVM regression does have a few distinct drawbacks. Especially when dealing with big datasets, it may be computationally costly, and the kernel function and hyperparameters selection can significantly influence the algorithm's performance. Furthermore, when the data contains noise or outliers, the performance of the SVM regression algorithm could not be excellent [184]–[186].

In general, SVM regression is an efficient tool for modeling complicated relationships and making correct predictions in regression tasks. This is especially true when standard regression approaches may have difficulty capturing non-linearities or highly dimensional interactions.

*D. Evolutionary Algorithms*

Evolutionary algorithms, often known as EAs, are a category of optimization algorithms that are created by drawing inspiration from the concepts of natural selection and biological evolution [187], [188]. Even though EAs are often employed for optimization tasks like function optimizing, tuning of parameters, and choosing features, they are additionally capable of being modified for regression tasks [189], [190]. The process by which evolutionary algorithms function in the context of regression involves the evolution of a population of potential solutions over the course of numerous generations to locate an optimal or near-optimal solution that minimizes the error amongst the results that were anticipated and those that were produced [191], [192]. A flowchart for EA-based regression is depicted in Fig. 7 [193].

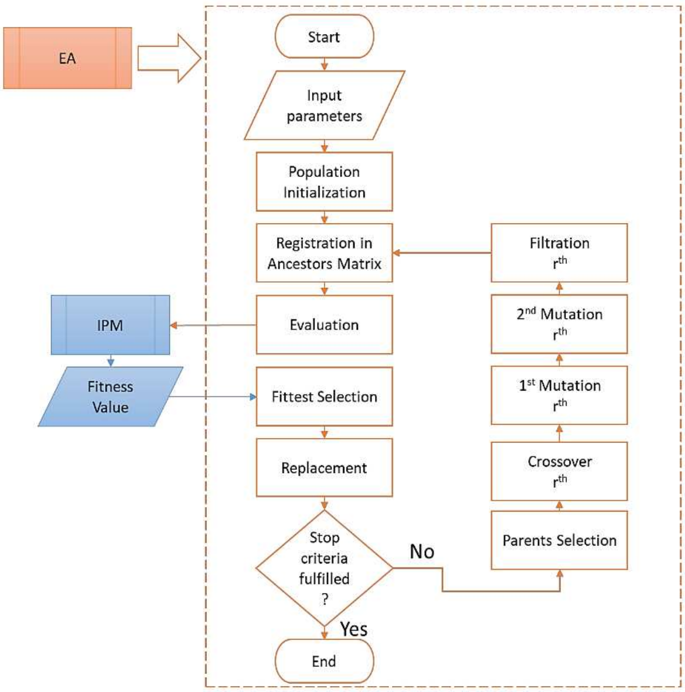


Fig. 7 EA-based ML framework [193]

It is common practice for the procedure to include the following steps [194]–[196]:

*1) Initialization:* Beginning with the initialization process, a population of possible solutions, each representing a potential regression model, should be established. In most cases, these solutions are shown as vectors of variables that describe the model structure [197].

*2) Evaluation*: Evaluate the fitness of each candidate solution by applying it to the training data and producing a fitness score determined by its performance in terms of regression error metrics like mean squared error or mean absolute error. This will allow you to determine whether or not the solution is suitable for use [198].

*3) Selection*: As part of the selection process, a subset of candidate solutions, sometimes referred to as parents, will be chosen to go through the process of reproduction based on their fitness ratings. In a manner that is analogous to the process of natural selection, situations in which solutions have higher fitness scores are more probable to be picked for reproduction [199], [200].

*4) Crossover*: In order to generate offspring solutions, it is necessary to carry out crossover or recombination procedures on the parents that have been chosen. By integrating aspects of two parent solutions, crossover is a process that results in the creation of new solutions that have the potential to function more effectively [201].

*5) Mutation*: To preserve the genetic variety of the population and to investigate new areas of the search space, it is necessary to add random variations or mutations to the progeny solutions [202], [203].

*6) Replacement*: To establish the next generation, it is necessary to replace some of the solutions that are already present in the population with the solutions that have been produced by the children. The selection of replacement solutions may be based on parameters such as elitism or fitness score [204].

*7) Termination*: Repeat the steps of evaluation, selection, crossover, mutation, and replacement for a predetermined number of generations or until a termination condition, such as convergence or a maximum number of iterations, is satisfied. This procedure is repeated until the completion of the termination process [205].

The capacity of evolutionary algorithms for regression to cope with high-dimensional query spaces, non-linear relationships, and chaotic or non-smooth objective functions is one of the many advantages that these methods provide [206], [207]. They can also explore different parts of the search space and avoid local optima, making them useful for complicated regression tasks, in which classic optimization methods may have difficulty. On the other hand, evolutionary algorithms could call for many function assessments and processing resources, mainly when dealing with high-dimensional or massive datasets. It is also possible for the efficiency of evolutionary algorithms to be sensitive to the parameter settings that are used as well as the evolutionary operators that are selected [208]–[212].

Evolutionary algorithms provide a versatile and powerful solution to regression problems. They can handle complicated connections and unclear data, making them ideal for certain situations. These algorithms can successfully improve regression models and identify solutions that reduce prediction error because they replicate the procedure of natural selection from which they get their results.

### E. Genetic Algorithms

Genetic algorithms (GAs), which are derived from the concepts of biological evolution as well as natural selection, have the potential to be modified for use as machine learning regressors throughout the process of solving regression challenges [213], [214]. GAs provides significant benefits in specific cases, notably when dealing with non-linear connections and high-dimensional data, despite the fact that they are not as often utilized as standard regression methods like linear regression or support vector machines. In the process of genetic algorithm-based regression, the algorithm repeatedly generates a population of candidate solutions, which are referred to as chromosomes, to optimize a fitness function that quantifies the quality of each alternative answer [215]–[217].

Several essential phases are involved in the process [218]–[220]:

*1) Initialization:* Creating a starting point of random chromosomal every one of which represents a potential solution to the regression issue, is the first step in the initialization process. Typically, these chromosomes encode possible solutions in the form of vectors that contain parameters [221].

*2) Evaluation*: Using a fitness function, which quantifies the degree to which each solution performs on the regression task, evaluates the viability of each chromosome in the population. This is the second step in the evaluation process. For the most part, this fitness function is determined by the difference between the projected output values and the actual output values [222].

*3) Selection*: It involves choosing a subset of chromosomes from the population to act as parents for the subsequent generation. The fitness of each chromosome is often taken into consideration throughout the selection process, with more fit chromosomes having a greater chance of being approved for selection [223], [224]. To generate offspring chromosomes, it is necessary to carry out crossover or recombination procedures on pairs of parent chromosomes chosen separately. To develop new candidate solutions, this includes the exchange of genetic information between the parents as mentioned earlier [225], [226].

*4) Mutation*: To preserve the genetic variety within the population, it is necessary to introduce random alterations or mutations to the chromosomes of the progeny. The algorithm is prevented from prematurely converging to solutions that are less than optimum by the use of mutation [227], [228].

*5) Replacement*: To generate the next generation, it is necessary to replace part of the chromosomes already present in the population with the chromosomes inherited from the offspring. The replacement process may involve picking the people who are the healthiest from both the parent population and the child population [229], [230].

*6) Termination*: Repeat the procedures of assessment, selection, crossover, mutation, and replacement until a predefined number of generations have passed or when convergence conditions have been satisfied. This is the seventh and last phase in the process. The criteria for convergence may include attaining a maximum number of iterations or achieving a level of fitness that is in accordance with the requirements [231].

The use of GA-based regression can be especially useful in situations when the search space is huge, non-linear, or discontinuous, and where conventional optimization methods may have difficulty locating the global optimal solution. In situations where the link between the variables that are input and those that are output is not well known, GAs are also an excellent choice for solving issues that include complicated, multi-modal fitness landscapes. On the other hand, as compared to standard regression approaches, GAs may need a more incredible amount of processing resources and longer execution times. This is especially true for big datasets or situations that are very complicated. It is also possible that the efficacy of GA-based regression is dependent on the selection of genetic operators, such as crossover and mutation, in addition to the design of the fitness function [232]–[234].

In conclusion, even though genetic algorithms might not be the best option for regression tasks in every circumstance, they provide a powerful and flexible approach to optimization that can be advantageous in certain machine-learning applications. This is especially true when dealing with complex, non-linear relationships and high-dimensional data.

## III. Results and Discussion

The complexity and ever-changing character of renewable energy systems are reflected in the fact that using soft computing in solar energy brings both obstacles and possibilities. Several intriguing pathways may be pursued to solve critical difficulties and unleash the full potential of solar energy usage. Some of these approaches include artificial neural networks (ANN), fuzzy logic, genetic algorithms (GA), and support vector machines (SVM) [235]–[237].

One of the most significant obstacles that must be overcome to use soft computing in the field of solar energy successfully is the inherently unpredictable and fluctuating nature of solar irradiation [238], [239]. As a result of the fact that solar radiation levels might change due to variables such as weather conditions, cloud cover, and seasonal fluctuations, reliable prognosis and forecasting can be challenging to achieve. To guarantee the dependability of solar energy production and grid integration, soft computing techniques need to be able to efficiently manage these uncertainties and adapt to the ever-changing circumstances of the environment [240]–[242].

One further obstacle is optimizing solar energy systems to achieve the highest possible levels of efficiency and performance. Several features of solar energy systems may be optimized using soft computing methods. These aspects include panel alignment, tilt angle, tracking mechanisms, and energy storage management [243]–[245]. Nevertheless, to achieve the ideal design of the system, it is necessary to consider several different aspects, including the geographical location, the climatic conditions, the patterns of energy use, and the economic restrictions. Soft computing methods need to strike a balance between these aspects and produce insights that can be put into action for the design and operation of the system [246], [247].

Furthermore, the incorporation of soft computing into the current solar energy infrastructure may be met with challenging technological and practical obstacles. To successfully implement artificial intelligence-based control systems, predictive maintenance algorithms, and energy management platforms, it is necessary to have robust hardware, dependable data connection, and smooth compatibility with preexisting systems and protocols. In addition, it is of the utmost importance to guarantee the cybersecurity and data privacy of solar energy systems that are enabled by artificial intelligence to protect against possible attacks and weaknesses [248]–[250].

The use of soft computing in solar energy gives much potential for innovation and growth despite the presented limitations. Creating intelligent solar energy forecasting models has significant potential that should be considered. Through historical and real-time data, soft computing approaches can enhance the precision and dependability of solar irradiance forecasts, hence facilitating more efficient energy planning, grid management, and resource allocation. In addition, improved forecasting skills may make it easier to incorporate solar energy into the larger energy ecosystem, which includes power markets and the architecture of smart grids [251], [252].

The optimization of the operation and maintenance of solar energy systems presents yet another possibility. The algorithms used in soft computing can assess sensor data, recognize performance irregularities, and provide recommendations for preventative maintenance measures to avoid system failures and outages. Solar energy operators can reduce operational interruptions, prolong the lifetime of equipment, and optimize energy production via predictive maintenance procedures. This results in considerable cost savings and better system dependability [253]–[255].

In addition, using soft computing methods has opportunities to enhance the efficiency and efficacy of solar energy conversion systems. The operation of solar photovoltaic (PV) arrays, concentrating solar power (CSP) systems, and solar thermal collectors may be optimized with the use of advanced control algorithms to maximize the amount of energy produced while simultaneously minimizing the number of resources that are consumed [256], [257]. Furthermore, soft computing techniques have the potential to assist in the development of solar materials, devices, and technologies of the future generation using better modeling, simulation, and optimization of design [258].

In addition, using soft computing in solar energy offers opportunities for developing intelligent energy management and grid integration solutions. Energy management systems that are powered by artificial intelligence can maximize the integration of solar energy into the grid, sustain dynamic pricing and demand response programs, and strike a balance between supply and demand [259], [260]. By using soft computing approaches, utilities, grid operators, and energy service providers can improve grid stability, resilience, and sustainability while simultaneously supporting the integration of renewable energy sources and decarbonization [261], [262].

In the case of solar energy, using soft computing provides several obstacles, including unpredictability, optimization, integrating, and cybersecurity. However, it also presents several significant potentials for innovation, development, and sustainability [263], [264]. Soft computing methods can play a revolutionary role in realizing the full capability of solar energy as a clean, plentiful, and sustainable energy source for the future. This can be accomplished by solving the obstacles that are provided and by capitalizing on the possibilities that are offered [265], [266].

Knowledge about global solar radiation serves as the foundation for various solar energy applications and is critical for environmental and economic problems. On the other hand, precise global solar insolation statistics are sometimes problematic or complex because solar radiation is subject to change, and observations are not always readily accessible [267], [268]. On the other hand, models that are based on machine learning can solve very nonlinear problems [269]. Deep learning, regarded as a potent method for moving machine learning closer to one of its original aims, Artificial Intelligence (AI), offers a feasible answer to this issue [270]. A study by Gujio-Rubio et al. [271] assessed the efficacy of several evolutionary neural network-based prediction models for sun radiation for the location of Toledo, Spain. The forecast was done by employing data from satellite-based observations and variables. Three kinds of neural computing systems are investigated: radial basis function units, neural networks containing sigmoid-based neurons, and product units. The findings of the sun radiation estimate at Toledo's radiometric station demonstrate that the evolving neural networks tested performed very well. With evolutionary training, the structure of the sigmoid unit-product unit was shown to be the best-performing model across all of those tested in this study. It generated an exact solar radiation forecast via satellite image data, surpassing all of the other tested evolutionary type NN, as well as alternative machine learning methods such as support vector machines (SVM) or evolutionary learning machines (ELM). Jumin et al. [272] employed a boosted decision tree regression model to forecast variations in sun radiation based on data obtained in Malaysia. The suggested model was then compared against other standard regression techniques, including linear regression and neural networks. Two distinct normalizing strategies (Binning and Gaussian normalizer), splitting size, and input parameters were studied to improve model accuracy. Uncertainty analysis and Sensitivity were employed to assess the suggested model's correctness. The findings showed that BDTR beat other algorithms with high accuracy. Rabehi et al. [273] employed several prediction models for sun radiation applications in a comparative study. This work evaluated the efficacy of ANN and BRT models and used a novel combination of the models above with LR to forecast daily global sun irradiation (DGSR). Different input combinations were examined to identify the most important input variables for DGSR prediction. The findings suggest that the MLP model outperforms the other models concerning two statistical indicators: normalized root MSE (0.033) along $R^2$ (97.7%).

In the field of solar energy, the incorporation of artificial intelligence (AI) has sparked a revolution, greatly improved technology, and redefined the landscape of solar energy collection and usage [274]–[276]. Solar energy systems have advanced significantly in intellect, effectiveness, and dependability due to artificial intelligence algorithms and methodology. This article goes into the many uses and advances of AI in the solar energy sector, emphasizing its competitive potential [277], [278]. At the forefront of AI's effect is the improvement of solar panel efficiency. AI algorithms play an essential role in establishing ideal operating settings for individual panels by continuously monitoring and evaluating solar irradiance, temperature, and the panels' efficiency. AI increases energy production while avoiding losses due to shading dirt, or panel deterioration, assuring optimal system performance and increased energy output [279], [280]. Accurate energy forecasting is essential for successful grid integration and energy administration in solar power plants. AI algorithms assess massive amounts of historical and present data, such as weather patterns, solar irradiance, consumption of energy, and market pricing, to produce accurate estimates of solar energy output. These projections provide grid managers, energy administrators, and solar power facility managers with crucial insights into energy distribution, grid balancing, and trading of energy, resulting in a more dependable and stable system infrastructure [281]–[283].

In solar energy systems, operational issues and component failures may hamper power output. Artificial intelligence-based fault identification and maintenance systems use machine learning methods to analyze real-time data through sensors and monitoring devices, quickly finding irregularities and diagnosing probable problems. AI algorithms improve system dependability by allowing for preventative maintenance and rapid fixes [284]–[286]. AI-enabled management technologies provide unique advantages for substantial solar farms regarding energy production and distribution optimization. AI algorithms enable efficient energy production and distribution, balance of load, allocation of resources, and predictive maintenance planning by assessing various data sources, including solar panel performance, meteorological conditions, energy consumption, and market dynamics. These management strategies increase operational efficiency, lower operating costs, and improve the overall efficiency of solar farms [287]–[289]. In addition, AI-driven energy storage management is critical for maximizing solar energy usage during low sunshine. AI algorithms assess data on energy prices, grid demand, and solar output to optimize the charging and discharging processes of energy storage components, boosting grid stability, lowering grid dependency, and enhancing self-consumption [290]–[292].

AI enables system designers to optimize panel setting up, system size, and configuration for solar energy projects based on criteria like solar perspective, shade studies, and energy consumption patterns. AI modeling and forecasting skills allow designers to analyze and choose the most effective and cost-effective solutions, increasing the project's viability and efficiency [293]–[295]. The incorporation of AI into solar energy systems ushers in a new age of possibilities and revolutionary potential, resulting in increased performance, lower costs, and more project feasibility [296]–[298]. AI applications in solar energy have the potential to further revolutionize the industry by driving productivity, trustworthiness, and sustainability in the worldwide energy landscape. They range from maximizing solar panel efficiency to intelligent energy projections, problem detection, handling solar farms, energy storage optimization, and layout planning [299]–[302].

TABLE I
THE FOLLOWING IS A SUMMARY OF THE APPLICATION OF SOFT COMPUTING TECHNIQUES IN THE DOMAIN OF SOLAR ENERGY

| Soft computing method | Application | Main outcomes | Source |
|---|---|---|---|
| ANN of six different learning algorithms | Solar radiation prediction | Prediction was 94% accurate. | [303] |
| ANN models with Logsigmoidal transfer function and TRAINLM training algorithm and | Prediction of global solar insolation | ANN model helped in prediction with low errors as Root mean squared error (RMSE) – 3.96% | [304] |
| Feed forward algorithm-based ANN | Monthly as well as daily solar insolation | Solar radiation prediction for 83 sites in China could be predicted with high precision | [305] |
| Random forest combined with firefly algorithm and ANN | Short-term prediction of solar radiation | The prediction was with low error as RMSE was 18.98% | [306] |
| Different types of ANN, ANFIS | Global horizontal irradiation forecasting | Accurate forecasting with RMSE as 2.78% and $R^2$ as 0.982 | [307] |
| GA and ANN | Data from 83 sites used for the prediction of global solar radiation | Forecasting accuracy of 99% and RMSE as 6.74% | [308] |
| Extreme gradient boosting (XGBoost) | Use of public data for solar radiation prediction | Highly accurate results provided by XGBoost | [309] |
| Gaussian process regression (GPR) and wavelet | Three years of data was used for model training and a fourth year of data was used for comparison | The hybrid approach of wavelet-GPR could predict with $R^2$ as 0.923 and RMSE as 2.4191. | [310] |
| ANN, Response surface methodology, and ANFIS | Energy yield and performance of solar farm | ANFIS could predict with $R^2$ as 0.983 and 0.6. | [311] |
| SVM based regression | Solar power generation prediction model | The model could predict with less than 3.08% error | [175] |

A large amount of attention has been drawn to the use of machine learning (ML) methods in solar prediction because these approaches have the potential to increase the accuracy and reliability of solar radiation forecasting [312], [313].

Some research has investigated various machine learning techniques and their applications in solar prediction, and each of these studies has produced distinctive results and insights. Since their introduction, Artificial Neural Networks (ANN) have become one of the most popular ML algorithms for predicting solar radiation [314]. A number of studies, including those conducted by Azadeh et al., have demonstrated the effectiveness of artificial neural network (ANN) models in accurately predicting solar radiation with high precision. [303] and Rao K et al. [304]. These studies have achieved prediction accuracies of up to 94% and low errors, as measured by RMSE of 3.96%, respectively.

In addition, the integration of ANN with other algorithms, such as Random Forest and Firefly Algorithm, has exhibited promising results in short-term solar radiation prediction, reaching low error rates with RMSE of 18.98%. This was reported by Ibrahim and Khatib [306]. In a similar vein, the combination of ANN and GA is effective, with predicting accuracies approaching 99% and RMSE as low as 6.74% [308]. Furthermore, recent machine learning approaches such as Extreme Gradient Boosting (XGBoost) and Gaussian Process Regression (GPR) have shown exceptional promise in the prediction of renewable energy [315]–[318]. Li et al. [309] proved the high accuracy of XGBoost in forecasting solar radiation using public data, while Ferkous et al. [310] employed a hybrid technique of Wavelet-GPR to obtain excellent prediction performance with $R^2$ of 0.923 and RMSE of 2.4191. The research conducted by Das et al. [175] demonstrates that other machine learning techniques, such as regression based on Support Vector Machines (SVM), have also been used to predict solar power production. This demonstrates the usefulness of support vector machines (SVM) in solar prediction tasks since their model obtained prediction accuracies with an error rate of less than 3.08%.

The scientific discussion on several ML-based approaches in solar prediction highlights the wide variety of obtainable methodologies and the distinctive contributions each of these methodologies makes to enhancing the precision and dependability of solar radiation forecasting procedures. These studies provide valuable insights into the strengths and limits of different machine learning algorithms, therefore paving the path for improved usage of solar energy and grid integration [319]–[321].

A look into the future reveals that the scope of this research will expand in some potential ways. In the first place, further research is needed to increase the capabilities of soft computing approaches for predicting, optimizing, and controlling solar energy. This involves creating more accurate and dependable forecasting models, optimization algorithms and control techniques that can dynamically adapt to changing environmental circumstances and needs for the system. In the second place, there is a need for the incorporation of soft computing approaches with new technologies such as the Internet of Things (IoT), big data analytics, and cloud computing to improve the scalability, flexibility, and efficiency of energy systems [322]–[324]. Using these synergies, researchers can construct intelligent and networked solar energy ecosystems, optimizing energy production, distribution, and usage in real-time. Furthermore, it is recommended that future research concentrates on tackling the practical issues involved with installing and deploying soft computing systems in solar energy infrastructure. This consists of establishing established protocols, interoperability standards, and cybersecurity measures to assure the dependability, security, and privacy of solar energy systems that are empowered with artificial intelligence. Additionally, there is a need for in-depth research on the economic, social, and environmental effects of solar energy solutions that are facilitated by soft computing. Policymakers and industry stakeholders can make educated judgments on investment priorities and policy interventions if they quantify the advantages of these technologies in terms of cost savings, improvements in energy efficiency, reductions in carbon emissions, and social benefits.

## IV. Conclusion

In conclusion, the investigation of soft computing approaches in the field of solar energy highlights the potential of these techniques to resolve critical difficulties and open up new prospects for developing renewable energy systems. Using methods from artificial intelligence, machine learning, and computational intelligence, researchers have made substantial progress in improving the efficiency, dependability, and sustainability of solar energy production, prediction, optimization, and management. These improvements have been made possible using these techniques. The problems that have been found, which include the fluctuation of solar irradiance, the complexity of system optimization, the integration barriers, and cybersecurity concerns, underline the need for continuing research and development activities in soft computing for solar energy. To properly address these difficulties, it will be necessary for scientists, engineers, policymakers, and industry stakeholders to work together across disciplinary lines to build robust solutions.

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