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A Comprehensive Review of the Artificial Neural Networks (ANN) Methodology Implementations for Analysing and Forecasting the Efficiency of Solar Water Heater Collector Under Various Tilt Angles

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Abstract: This article examines tilt angle and reviews artificial neural network (ANN) models for tilt angle (TA) prediction and optimization in solar water heaters (SWH). The paper provides a summary of design simulations, parameters, applications, and mathematical approaches that are used in a variety of applications. The quantity of references analysing TA deployment in context of research publications are increasing. The number of countries involved in solar system operations has increased dramatically. Many models and test procedures for determining the optimal TA in various solar schemes has been created, each of which is identified by their mathematical models and tracking techniques, as evidenced by recent research. The 4 ANN models like Extreme learning machine (ELM), radial basic function (RBF), Multilayer Feed forward neural network (MLFNN), and Artificial Neuro-fuzzy inference System (ANFIS) are compared by estimating the root mean square error (RMSE) value of training and testing of models. The ELM performs better compared to other models. The variables of TA like slips, inclination, height, and width are also mentioned in this article. The analysis of SWH at various tilt angles and development of ANN model for optimization of the TA is also discussed in this article. Here 35 research paper related to development and analysis at various tilt angle has been reviewed and understand their impact of different ANN approaches on the performance of SWH.

Keyword: *Tilt angle (TA), ANN models, RBF, MLFNN, ANFIS, ELM, Solar heater system, Solar energy (SE), solar collector (SC), solar radiation (SR)*

1. Introduction

Due to the finite stocks of fossil fuels and their rapid depletion, it is important to create effective methods for utilizing alternative energy sources. There are many different forms of renewable energy, with solar energy (SE) being one of most plentiful or clean. There are two ways to use solar energy: active and passive. Sun rays are directly utilized in passive SE utilization without need for any equipment. In active SE utilization, sun rays are not for conventional use, and an active type of mechanical equipment is required for conversion of SE into various kinds of energy. Solar collectors are an example of an active energy consumption method. Solar collectors play an essential part in solar energy application system. An SC is a type of heat exchanger that captures radiation or transmits thermal energy to a graceful fluid [1].

Solar energy is a pollution-free energy source that has a lesser environmental effect than fossil fuels. Solar energy conversion is now commonly utilized to create both power and heat. The development of thermal conversion methods has resulted from the ever-increasing demand for energy. Thermal collector research is centred on improving the thermal efficiency of solar air collectors because of their simple form and vast variety of uses, which include everything from house heating to agricultural product drying. Furthermore, only a few businesses have used solar air collectors to pre-heat workspaces. One of the primary problems for any thermal system is the efficient collection and usage of heat. As a result, every thermal energy system must take into account of energy and analysis, as well as the quality and amount of energy extracted/converted from solar air collectors [1].

Investigational or analytical research [2], followed by use of computer tools, all require lengthy time to arrive to a precise response to a physical problem. ANN on other hand reduces period while also providing crucial material patterns in multi-dimensional information domain; as a result, approaches has grown in popularity in recent years in science, particularly in Computer Engineering applications.

Simplicity, fast speed, and capacity to handle complicated and nonlinear relationships between variables and retrieved data are the main benefits of the ANN approach when compared to other computational techniques [2]. The approach's main drawback is that it requires data for model training, which is not the case with any other analytical method.

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It is necessary for the design and development of SE systems to have a deep understanding of the variations or excessive uses of SR which really fall on it. Estimate of SR on a horizontal surface is done using a variety of approaches like hourly, monthly latitude, etc [3][4][5]. The direction and tilt angle of a solar thermal collector and solar photovoltaic (PV) panel impact the quantity of solar energy it receives [6][7]. It focused near equator in general, with north hemisphere facing south or southern hemisphere facing north. Though, because SE varies according to the time of day, month, season, and year, the best TA for catching extreme solar radiation will differ for each location.

Several scholars have utilized ANN to forecast performance in the realm of energy consumption and heat pump systems, conversion system [8][9], wind, PV system [10], air-conditioning, refrigeration [11], PV power systems [12], solar radiation predictions [13], and numerous thermal systems [14][15][16]. Ensuing the literature, it was discovered that no independent review on SC systems utilizing artificial neural network methods had been published.

ANN technique differs from traditional computer approaches that adopt a new and better approach. Unlike previous numerical solutions, this technique does not require computer programming to finish the findings. This concept may also be applied to issues that are difficult and time-consuming to tackle using traditional methods. Especially well-suited to dealing with incomplete data sets, imprecise and missing information, and circumstances that are complex and well-defined, where individuals frequently make judgments based on intuition. The technique is self-adaptive, can handle enormous volumes of data, is an elastic computational tool with high computing accuracy. When arithmetical connections between input or output variables are unidentified or cannot be integrated, it is particularly well suited for modelling and prediction.

Fig.1 illustrates the main phases of the ANN simulation approach. In ANN prediction, crucial stages are mentioned below [17].

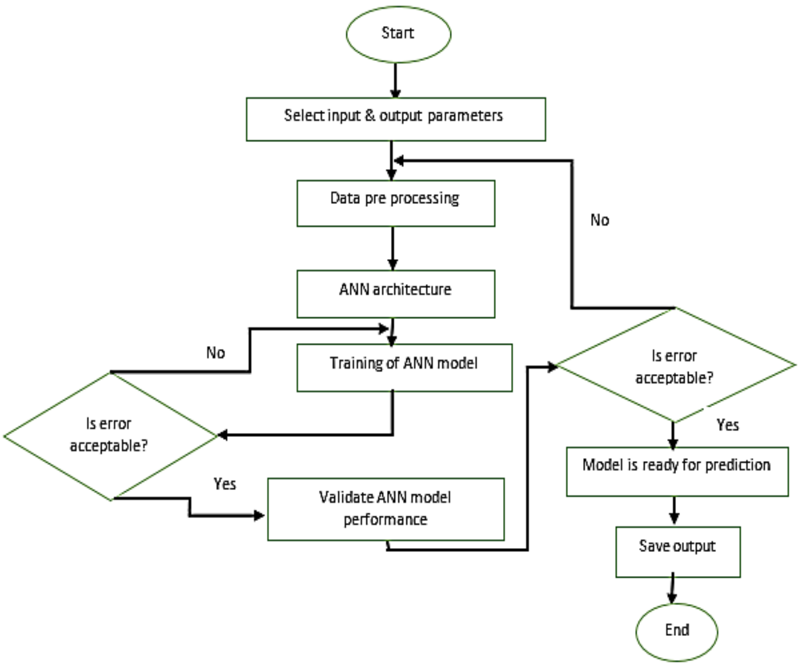

Fig.1. Main phases of ANN architecture

- The variables are chosen initially in the ANN method.
- Analytical and experimental procedures are then used to acquire data sets.
- Pre-processed data is organized into input and output data sets.
- Training, testing, and validation sets are created from the input data.
- The model is created by employing multiple learning algorithms with varying numbers of hidden layers neurons to train using standardized input data.
- The model's performance is evaluated using statistical error analysis.
- At this point, the ANN model is ready for prediction.
- Finally, the best model's projected data is retrieved and compared to real data received through trials.

1.1. Solar Collector (SC)

SC is device that absorbs SR, transforms it into thermal energy, then transmits it to an occupied fluid. Heat collected by occupied fluid also is utilized to charge thermal energy storage systems for usage. PV modules are used in photovoltaic (PV) systems to convert solar energy into electrical energy. It also creates a lot of waste heat, which can be applied by connecting a PV board to carrier fluid-filled tubes.

Fig.2 depicts the various types of solar collectors. Fixed collectors and tracked collectors are the two types of solar collectors that are often used. Fixed collectors remain stationary; whereas tracking collectors follow movement of the sun like that incoming solar radiation always strikes them perpendicularly. Single or double axis are 2 types of SC track. Compound parabolic collectors, evacuated tube collectors or flat plate collectors are three types of fixed collectors. There are three types of single-axis tracking collectors: cylindrical trough collectors, linear Fresnel reflectors or parabolic trough collectors, the central tower receiver, circular Fresnel lens or parabolic dish reflector, are all sub-categories of the double-axis tracking collector. These solar collectors can be used in a variety of ways, depending on the practicality and amount of energy needed [18].

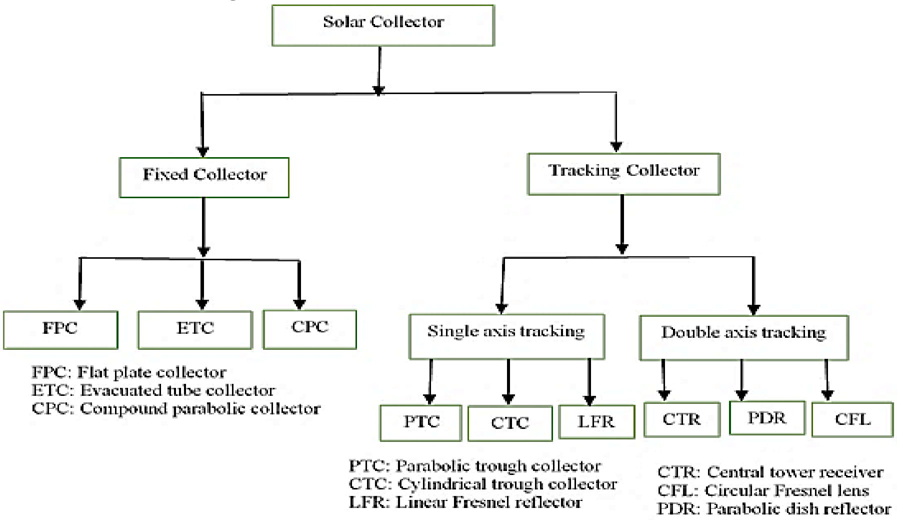

Fig.2. Various types of solar collector

Except that it only represents one physical component, solar collector performance model is identical to one contained in program. The solar collector has same interactions with the environment or other components as computing module. Solar collectors are often greatest significant mechanisms of active solar heating systems. Gather solar energy in the form of radiation, convert it to heat, and then transfer it to a colder fluid (water and air). Pool heaters, solar water heaters or space heaters have all benefit from this energy.

1.2. Solar Water Heater (SWH)

In current time, energy conservation is a top priority, and boiling water for both household and industrial purposes consumes a significant amount of energy. Solar water heaters are the solution to the aforementioned dilemma since solar energy is abundant and free in most parts of the world. SWH transforms solar energy into thermal energy, which is used to heat transfer fluids or heat water.

SWH is having two types based on circulation of water: (1) Active SWH (thermosyphon system), (2) Passive SWH.

The Passive SWH operates on the process of Thermosyphon, states that the cold water in SWH absorber tubes is heated by solar radiation, where it is replaced by cold water, and the cycle repeats until the temperature of the water in the absorber tubes and water tank is equalized. Active SWH circulates water in the system using an external source such as a pump. SWH may be divided into two types based on their construction: (1) concentrating collectors and (2) flat plate collectors.

The v-through sun water heater is a flat plate passive solar water heater that uses mirrors to focus solar energy on the absorber tubes. The performance of the v-through SWH has been investigated for altering its tilt angle from the dust deposition on glass plate [19]. Fig.3 shows the experimental setup of SWH.

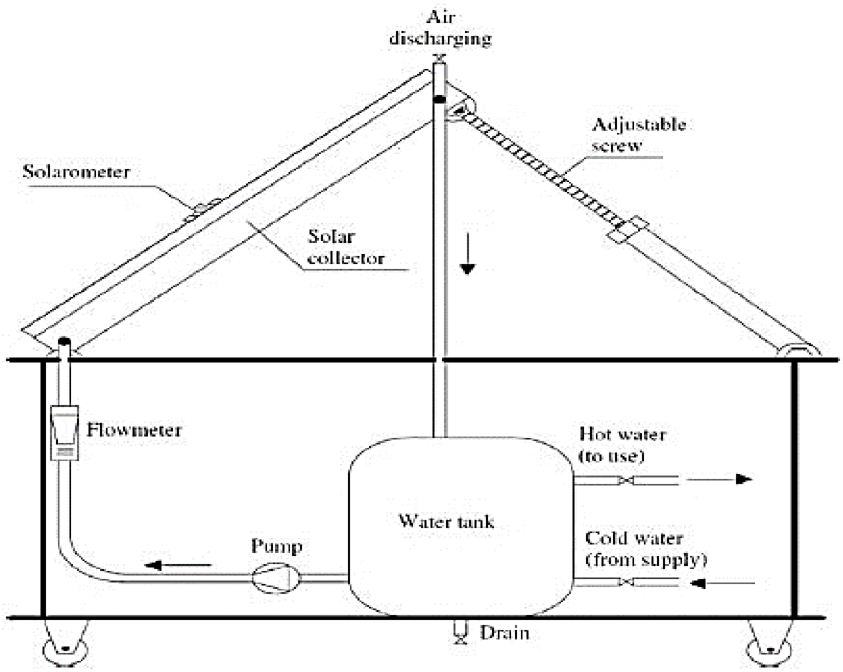

Fig.3. SWH experimental setup

2. Literature Review

ANN approaches have emerged as viable alternatives to traditional methods in a variety of solar energy applications. The usage of ANN in renewable energy systems has been evaluated by Yadav & Chandel [20]. Mellit et al. [21] looked into ANN for solar system size, while Mellit and Kalogirou [22] looked at ANN for PV applications. It can be used to model, predict, and forecast data in a variety of ways.

2.1. Global solar prediction

One of most significant variables in the operation of a solar energy system is obtainability of global SR on ground surface. As a result, this part focuses on use of ANN methods to forecast global solar radiation utilizing a variety of meteorological and geographical factors.

Sözen et al. [23] used atmospheric or geographic data as input variables to construct an artificial neural network model for estimating SR in Turkey. Pola-Ribiere conjugate gradient, logistic sigmoid transfer function, Levenberg–Marquardt and Scaled conjugate gradient, are the learning algorithms for network. The multilayer perceptron (MLP) network's MAPE value is determined to be 6.73 percent.

Shariati et al. [24] goal of this study is to look at how artificial intelligence (AI) approaches, which are sub-branches of SC methods, may be used to forecast the behaviour of a new form of C-shaped shear connector called TA Connectors. Some push-out tests are performed on these connectors for this reason and needed data for various artificial intelligence models is obtained. Then, to determine the main influencing parameters on shear strength of TA connections, an ANFIS is created. The ANFIS data are used to build a total of six distinct models. Finally, to forecast the shear strength of connections in each of 6 models, AI approaches such as an ANN, an ELM, and another ANFIS are used.

Zejli et al. [25] constructed an artificial neural network model to estimate monthly sun irradiance at 41 Moroccan locations. The data ranges from 1998 to 2010, the networks' inputs are normalized longitude, elevation measurements and latitude. Solar irradiation is expected to range from 6230 to 5030 Wh/m^2/day.

Mohandes and Rehman [26] utilized 4 mixtures of input data (relative humidity maximum, day, mean air temperature, air temperature). With an MSE of 5:18 107, findings suggest that utilizing daily mean temperatures and relative humidity performs well than alternative combinations.

Lazzs et al. [27] predict hourly global SR (HGSR) for La Serena in Chile, utilized an artificial neural network model with air temperature, soil temperature or relative humidity as inputs. The R^2 value is 94 percent, suggesting that meteorological and hourly global solar radiation data are highly correlated.

Azeez [28] guess monthly average global sun irradiance (MAGSR) on a horizontal surface, Nigeria used feedback Propagation NN. Sunlight duration, relative humidity, and maximum ambient temperature are input factors, while solar irradiation is the output value. The results (R1 499.96, RMSE1 40.0028, MPE1 40.8512) showed that calculated and observed levels of worldwide sun irradiation were in good agreement.

Linares-Rodrguez et al. [29] used ANN to forecast SR in Spain based on inputs such as latitude, total column ozone, longitude, total cloud cover, daily clear sky radiation, and skin temperature. RMSE of ANN forecast and measured values range from 13.52 percent (for training stations) to 14.20 percent (for testing stations). In Andalusia, model validation is based on 9 years of measured data from different 83 metrological stations (MS) (Spain). For places where meteorological data is available, the approach can used to produce global solar radiation. When only rare MS are utilized for training and these stations do not cover whole research region, Artificial Neural Network valuation is shown to be distance dependent or cannot be inferred. As result, data from a great number of stations covering region must be utilized to accurately estimate SR for sites located at larger distances, and solar maps must also be created with good accuracy for region of interest.

Oztop et al. [30] in Mediterranean area of Anatolia, Turkey, created artificial neural network-based model for estimating SR for 7 towns. To determine the optimum ANN configuration for estimate, six distinct combinations of latitude, months, longitude, average temperature, altitude, average wind velocity, sunlight duration or average cloudiness are utilized as input factors. Several input factors affect the R^2 value when estimating SR.

Voyant et al. [31] investigated exogenous meteorological factors for prediction of everyday sun radiation. For Corsica Island, France, the normalized (nRMSE) is determined to be 0.5 percent, 1 percent, and adding both endogenous and exogenous factors reduce nRMSE by 1 percent, increasing prediction accuracy.

Rumbayan et al. [32] utilized ANN to calculate Indonesia's monthly sun irradiation. The model uses NASA data and nine input variables, including average temperature, latitude, average wind speed, regular relative humidity, longitude, average sunlight duration, month of year or average precipitation. With 9 neurons in the buried layer, the MAPE is determined to be 3.4 percent. For 30 provinces in Indonesia, GIS technology for solar mapping is presented.

Rehman or Mohandes [33] utilized the RBF network technique to estimate diffuse or direct normal SR for Saudi Arabian locations based on the following input data: relative humidity, ambient temperature, global solar radiation and day. RBF (0.1 spread constant or 50 hidden neurons,) forecasts direct regular sun radiation with the MAPE of 0.016 and 0.41 for long-winded solar radiation.

Senkal et al. [34] forecast locations in Turkey, employed generalized regression neural networks (GRNNs) to estimate SR based on longitude, latitude, month, meteorological satellite data or altitude. The RMSE values vary between 0.0144 and 4.91 percent.

Sumithira and Kumar [35] in Tamil Nadu, India, employed the ANFIS for monthly global sun radiation forecast (MGSR). ANFIS model uses solar radiation as an output parameter and uses relative humidity, ambient temperature, wind speed or atmospheric pressure as input parameters. In the ANFIS model, the R^2 value is 98.98 percent. Table 1 shows the literature related to global solar prediction.

Table: 1 Research related to Global solar Prediction

References	Authors	Research data
[24]	Shariati et al.	To determine the main influencing factors on the shear strength of the TA connections, an ANFIS is created. The ANFIS data are used to build a total of six distinct models. Finally, to forecast the shear strength of the connections in each of the six models, AI approaches such as an ANN, an ELM, and another ANFIS are used.
[25]	Zejli et al.	Constructed an artificial neural network (ANN) model to estimate monthly sun irradiance at 41 Moroccan locations. The data ranges from 1998 to 2010, the networks' inputs are normalized
[26]	Mohandes and Rehman	Utilized 4 mixtures of input data (mean air temperature, relative humidity maximum, day, air temperature). With MSE of 5:18 and 107.
[27]	Lazzs et al.	Utilized an ANN model with air temperature or relative humidity as inputs. The R^2 value is 94 percent.

[33]	Rehman and Mohandes	Utilized the RBF network technique to estimate diffuse or direct normal solar radiation. RBF (0.1 spread constant or 50 hidden neurons,) forecasts direct regular sun radiation with MAPE of 0.016 and 0.41.
[34]	Senkal et al.	Employed GRNNs to estimate SR based on longitude, latitude, month. RMSE values vary between 0.0144 and 4.91 percent.

2.2. Solar water heater

Bracamonte et al. [36] calculate TA with numerous designs in SWH which claims particularly in construction of collectors or tubes in collectors. Impact of tilt angle (10°, 45° or 27°) on thermal effectiveness or water delamination in a glass evacuation tube passive SWH was studied.

Mancrichahri et al. [37] used minor tilt angles of 5°, 2°, 10°, 15° or 0° concerning vertical and affect results of falling film drain water (FDW) retrieval systems.

Tang & Yang et al. [38] examined thermal presentation of water in glass-evacuated tubes in SWH at night, finding that bigger collector tilt-angle, higher reverse flow rate. You et al. [39] shows TA has little effect on presentation of SWH in China.

In Belgrade, Skerli et al. [40] examined several TA for gatherers at 2°, 12° or 4° positioned in a north–south orientation, and annually adjusted for heating household hot water.

Tang et al. [41] demonstrated presentation of two equal SWH in design at various collector tilt angles from horizon, one at 22 degrees or other at 46 degrees.

Khatib [42] established measured model for banished glass tube collectors at Solar Water Heater to determine optimal TA to exploit annual solar radiation in China, discovered that optimum tilt angles for sites with latitudes better than 30° are now about 10° fewer than that of latitude for sites. Table 2 shows the literature related to SWH.

Table:2 Research related to SWH

References	Authors	Research Data
[36]	Bracamonte et al.	In a glass evacuation tube passive solar water heater, the influence of tilt angle (10°, 45° or 27°) on thermal efficiency and water delamination was demonstrated.
[37]	Mancrichahri et al.	The effects of minor TA of 2°, 10°, 5°, 0°, and 15° relative to vertical on routine of falling film drain liquid HRS were shown.
[38]	Tang & Yang et al.	At night, researchers looked at thermal performance of the water in a glass displaced tubes in solar water heater, finding that larger tilt-angle of collector, higher the opposite current rate.
[39]	Zhang et al.	In China, it was demonstrated that tilt angle did not affect routine of SWH.
[40]	Skerlic et al.	In Belgrade, Serbia, researchers investigated several tilt angles for collectors at 2°, 12° or 4° set in a north–south orientation, and yearly adjusted for heating residential hot water.
[42]	Khatib	At SWH, established a scientific model for evacuated glass tube collectors to determine the optimal TA to exploit yearly solar radiation in China, or discovered that best tilt angles for sites with latitudes more than 30° are around 10° fewer than latitude for locations.

3. Tilt angle

The number of photons received by PV panel surface has a significant impact on its efficiency. In reality, the tilt of a solar panel has a clear impact on the yield measurement. Solar panels must be angled at optimal angles in this manner in order to collect most extreme solar energy available in a given area. A dynamic sun tracker is the most effective method for improving solar panel tilt. Dynamic sun trackers are mechanical or electromechanical devices that adjust tilt of a solar array or solar panel at regular intervals throughout the day. On the other side, the disadvantages of the system, includes energy loss and capital cot due to tracking process. For example, changing the tilt angle of a PV panel from daily to monthly, may be more feasible than using a dynamic sun tracker [43]. Estimating the solar radiation on the inclined surfaces is an essential part of tilt angle selection, since it influences the quantity of solar radiation received by PV module surfaces. Because one of the elements that has a significant impact on TA values is the site's latitude, each place has its own unique tilt angle. The tilt angle value for various cities has been computed by a few academics from across the world. Fig.4 shows the TA diagram.

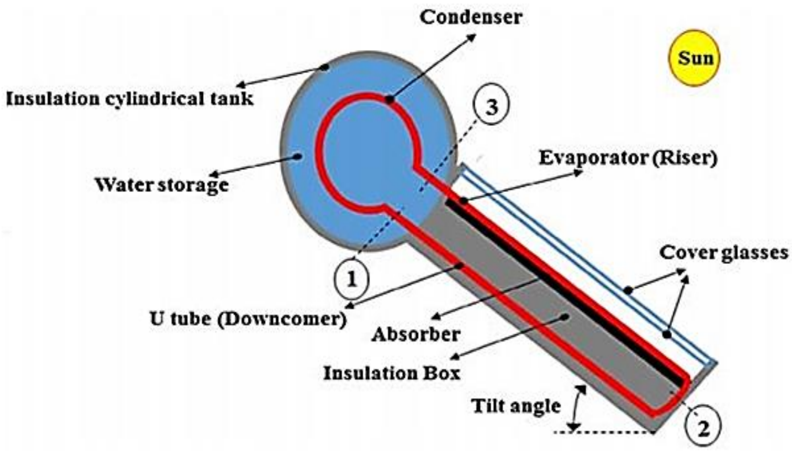

Fig.4. Tilt angle diagram [44]

3.1. Tilt angle Application

This section gives an overview of maximum successful knowledge and methods used in recent studies on mathematical approaches, design parameters, simulations, or applications for tilt angle in various applications. Selection of finest components or materials, best analysis utilizing simulation tools, and mathematical approaches has all contribute to the best design for any solar system. Current study examines the impact of tilt angle on design.

Most solar systems follow the path of the sun to concentrate heat on a receiver, which contains a thermodynamic process or generating unit, in order to collect the sun's maximum solar radiation. This knowledge can be used in a variety of capacities, including small, medium, and big. On the other hand, larger capacity can be reached by combining small units to create a solar collector farm. Solar Cooker [45], building-integrated photovoltaic system (BIPV) [46], SWH [47], Photovoltaic systems [48], solar updraft tower power plant [49], solar cooling [50], solar-powered thermoacoustic engines [51], Solar Still [52], and solar collectors are just a few examples of applications where the optimal tilt angle for a detailed topographical is important.

3.2. Optimization of tilt angle using ANN technique

ANN approaches are great research tools because can handle clustering, data classification, non-linear function approximation, and simulation problems [53]. These are utilized in a variety of sectors of research or technology [54], as well as for predicting solar radiation [55].

Chang [56] determined the optimal TA for highest output power energy of PV modules in 7 locations of Taiwan using sequential NN approximation or orthogonal arrays (SNAOA). To find best TA design, a back propagation NN is utilized. To optimize power on a PV module, maximum and lowest morals of optimal TA or voltage are utilized constraints. For Taipei site, yearly optimum angle is found to be 23.25°C.

Zervas et al. [57] predict with TA or orientation as input parameters, employed RBFNN to forecast SR on slanted surfaces. The RBFNN is trained using a fuzzy method, it is discovered that altering the tilt angle seasonally enhances the routine or regularity of PV array output power.

Mehleri et al. [58] shows for calculating global solar radiance on inclined surfaces in Athens, use worldwide solar radiance on horizontal surface, extra-terrestrial radiation, solar incidence or solar zenith angle on slanted plane as inputs to RBFNN. Absolute proportion of variance (R^2) is 96 percent, indicating that the model's assessment is correct.

Notton et al. [59] predict the Mediterranean site of Ajaccio, France, constructed 3 ANN models to predict hourly global irradiation (HGR) on tilted plane. 1^{st} or 2^{nd} models calculate hourly worldwide irradiation on 45°C, 60°C tilted planes, however 3^{rd} model calculates together. ANN models used reclination hour, zenith angle, angle, hourly extra-terrestrial parallel irradiation, or HGR on 45°C, 60°C tilted planes as inputs or HGR on 45°C, 60°C tilted planes as outputs. First, second, or third ANN models had R^2 values of 99.79%, 99.82%, and 99.70%, respectively.

Celikand Muneer [60] utilized GRNN to forecast SR on a slanted surface for location Iskenderun, Turkey. GRNN uses global sun irradiation on horizontal surface, or hour angles, declination as input parameters. R^2 or MSE, respectively, are 98.7% or 14.9 Wh/m^2.

Chatterjee [61] utilized ANN to predict optimal tilt or entire irradiance on a tilted surface using 14 inputs (12 months irradiance value, or ground reflectivity). The output layers are hyperbolic tangents, the training technique or activation function in hidden is linear and Levenberg–Marquardt. The difference between the anticipated and analytically calculated optimal tilt angle is found to be 31, indicating that ANN methods provide reliable estimates. As a result, ANN methods minimize the computation portion of optimal tilt angle calculations and provide more accurate estimates of tilted surface and optimal angle of the solar radiation at various locations. Table 3 shows the summary of optimum of TA using ANN technique.

Table: 3 Summary of optimum of TA using ANN technique

Reference	**Author**	**Location**	**R^2 value of TA and Models**
[56]	Chang	7 locations of Taiwan	Optimum angle is 23.25°C model used Sequential NN.
[58]	Mehleri et al.	Athens	Value is 96 percent, models used RBFNN.
[59]	Notton et al.	Ajaccio, France	Values of 1st, 2nd and 3rd models 99.79%, 99.82%, and 99.70%, 3 ANN models are used.
[60]	Celik Muneer	Iskenderun, Turkey	Value is 98.7% or 14.9 Wh/m^2 model used GRNN.
[61]	Chatterjee	Different location	TA is 31, ANN model is used.

3.3. Optimization of TA using other techniques

Shukla et al. [62] conducted a comparative analysis of 6 different solar radiation estimate models at a tilt angle of 23.26°.

Smith et al. [63] used a computational technique for estimating the all-sky irradiance to estimate horizontal irradiance, optimum tilt angle or tilted irradiance. The optimal tilt angle for scheduled, seasonal, half-annual, and annual modification was established by Khahro et al. [64], and it ranges from 0° in June, July or May to 49° in Dec. Annual optimal tilt angle was discovered to be 23°, that is close to the examined location's latitude (25° 07′N) Pakistan.

Mondol et al. [65] looked at variation in regular or periodic solar radiation and PV production, as well as the influence on possible savings in household power bills in Northern Ireland, discovered that somewhat westerly (190°) angles are best.

Soares et al. [66] used a daily integration technique to use daily sun radiation data, calculate HSR. Li et al. [67] used sunlight hour data model to compute SR or optimal TA on a slanted surface with various orientations. Maximum inaccuracy in this model was determined to be fewer than 5.2 percent.

Chandel et al. [68] created model that uses sunlight hours and temperature data to calculate HSR. Yadav and Chandel [69] examined TA needed to optimize SR, which changes based on period or place.

Chang [70] likened fixed PV panels to single axis tracking. Author also looked at the gain in interplanetary radiation and discovered that, except at solar noon, the incidence angle of sunlight on tracked panels is less than stationary panels.

Li and Lam [71] in Hong Kong, discovered that optimal TA of a SC is around 20° due south to obtain yearly solar yields of over 1598 kWh/m^2, or that TA is almost equivalent to latitude of location to obtain extreme annual solar radiation. The metrological data was used by Wu et al. [72]. By maximizing alien solar radiation, Gunerhan & Hapbasli [73] determined the optimal tilt angle. Sugden [74] looked at how view factors are calculated and how they affect solar radiation. Table 4 shows the optimization using other techniques.

Table: 4 Summary of optimization using other technique

Reference	**Author**	**Tilt Angle**
[62]	Shukla et al.	Six different SR estimate models at a TA of 23.26°
[64]	Khahro et al.	Annual optimal tilt angle was discovered to be 23°

[65]	Mondol et al.	Discovered that somewhat westerly 190° angles are best
[67]	Li et al.	Model determine value to be fewer than 5.2 percent
[71]	Li & Lam	Optimal TA of a solar collector is around 20°.

3.4. TA optimization using particle swarm optimization (PSO), Genetic Algorithm (GA) and Simulated Annealing (SA)

Optimization is a process of determining conditions that produce the objective function's greatest or minimal value to achieve correct outcomes under defined conditions. Any engineering system can benefit from it in terms of design, building, and maintenance [75]. SR on tilted surface is used as an objective function for determining optimal tilt angle, which is addressed using several optimization approaches like SA, PSO or GA.

The GA is well suited to optimization problems involving complicated nonlinear variables because it has a high chance of finding global optimal solutions [76]. Instead of a single design point, a population of points is utilized to start GA [77]. It is based on natural genetics and natural selection concepts.

Talebi zadeha et al. [78] utilized GA to determine the optimal hourly, monthly, daily, seasonal, and annual tilt angle for Iran, demonstrating that optimal hourly surface azimuth angle is not 0 or that the optimum TA of PV panels or solar collectors is similar. SE gain at daily and monthly optimal TA is same, while the energy gain at the hourly TA is higher. As a result, the sun tracker is useful for hourly TA fluctuation.

Ongradac et al. [79] using GA or fuzzy logic, determined optimal blind tilt angle (rotation of angle in anticlockwise or clockwise directions) for preserving precise room illumination. This procedure is beneficial in terms of preserving user comfort while also conserving electricity.

Chen et al. [80] utilized Simulated Annealing (SA) is a technique for locating the worldwide optimum with tall likelihood of objective functions including multiple local minima. It is named after the modelling of thermal annealing of disapprovingly heated materials. SA was utilized to determine the best installation angle for permanent solar-cell panels.

Chang Y. [81] presented a PSO technique with nonlinear time-varying evolution (PSO—NTVE) to estimate TA of PV modules for extreme output electrical energy of the Taiwan region. Taichung, Tainan, Kaohsiung, Heng Chung, Hualian, and Taitung have early optimum angles of 18.16°C and 17.3°C, 16.15°C, 15.79°C, 15.17°C, 17.16°C, 17.16°C, 15.94°C respectively. For obtaining an optimal solution, the PSO—NTVE is quicker than the additional 3 PSO techniques or GA approach. As a consequence, these optimization approaches will outperform additional methods (maximization of radiation by shifting from 0°C to 90°C in defined increments, latitude-based method). Table 5 shows the optimization using PSO, GA and SA.

Table: 5 Summary of optimization of TA using PSO, SA and GA

References	Author	Technique used
[78]	Talebi zadeha et al.	GA to determine the optimal hourly, monthly, daily, seasonal, and annual tilt angle for Iran.
[79]	Congradac et al.	Used GA or fuzzy logic, determined optimal blind tilt angle
[80]	Chen et al.	Utilized Simulated Annealing (SA) is a technique for locating the worldwide optimum TA.
[81]	Chang Y.	Presented a PSO technique with PSO—NTVE to estimate tilt angle.

4. Artificial neural network (ANN)

The ANN method is used to model, optimize, simulate, and forecast a system's performance. Because of its quicker processing speed and excellent precision, it has grown in popularity during the previous two decades. ANN are data processing systems that are comparable to technology used in the human brain. Dendrites, synapses or cell body or soma, are additional components of biological networks that include neurons. Dendrites receive input signals and material, the cell body functions as a workstation, synaptic connections serve connection, and the axon transmits output signals to other neurons while performing non-linear processes [82].

Fig.5 depicts a [83] normal biological neuron in the human brain. The neurons in an ANN model are a vast number of processing components. ANN functions in the same manner that the human brain does: it learns and stores information called weights. Each neuron gets numerous inputs proportional applies nonlinear activation function, connection weights from other neurons, creates a single output data that can be sent to additional neurons. These input data are processed by the neurons, which then pass them on to the next layer of the network.

The biological neural network of humans inspired ANN as the artificial intelligence (AI) tool. Function approximation, classification, and time series prediction are three key fields of research where ANN has been successfully used. AI approach with the layer to layer structure may learn patterns or predict outcomes in a high-dimensional space of issue where determining link between parameters is difficult. MLPs are a kind of FF ANN that consists of an input layer, an output layer, or at least one hidden layer. One or more neurons can be found inside each of the layers. The input values (nodal values) are received by the first layer of ANN and sent to the accessible neurons in the following layer.

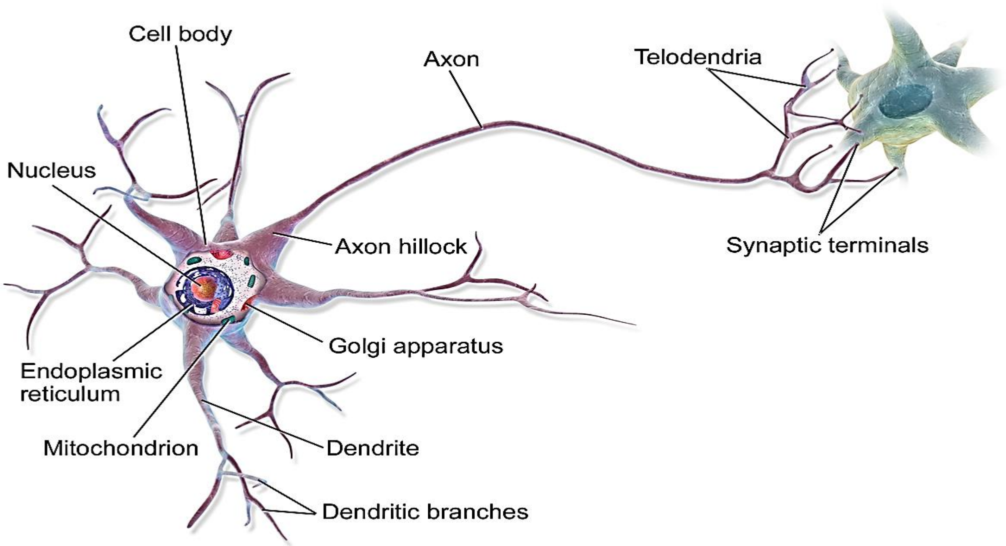

Fig.5. Normal organic neuron in human brain

4.1. Artificial Neuro-fuzzy inference System (ANFIS)

The ANFIS maps inputs into target values using a neural network learning method and fuzzy logic. There are five levels of the ANFIS structure. Fig.6 depicts basic structure of ANFIS [84].

- The fuzzy layer is the structure's initial layer. It is computer program that combines NN or fuzzy logic to create a hybrid intelligence system. Adjustable nodes in this layer are represented by square nodes with x or y inputs and names A_1, A_2, B_1 and B_2.
- The second layer is referred to as the product layer, whole node is a fixed node designated M and represented by a circular node. The outputs of the fixed nodes are w_1 and w_2, which are weight functions of following layer.
- Normalizing layer is third layer of network, all of the nodes in this layer are fixed nodes. These nodes, which are identified by the letter N, normalize firing strength by computing ratio of firing strength to total of others strength.
- De-fuzzy layer, which is characterized through a square node, is fourth level.
- 5^{th} layer is only fixed node that adds total number of nodes and the sum of all incoming data.

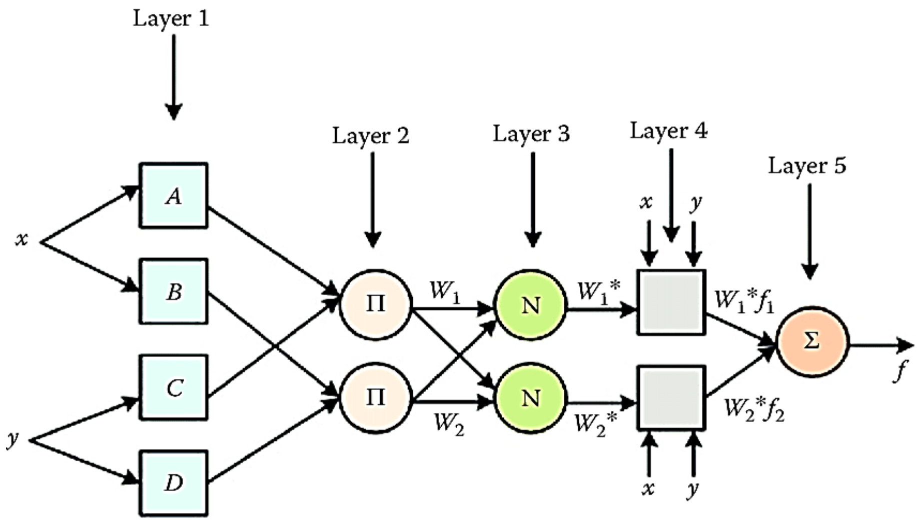

Fig.6. ANFIS model

4.2. Multilayer feed forward neural network (MLFNN)

Illustrated MLFFNN model has 3 layers: one or more hidden layers, an input layer, or an output layer [84]. Individually neuron gets data from further neurons or transmits it via hidden levels before reaching the output layer. An ANN is made up of neurons, which are interconnected processing nodes. Fig.7 depicts the fundamental construction of a MLFFNN. Each neuron's output is the consequence of a weighted collection of inputs. The total of the neurons' weighted inputs is given as:

$$X = \sum_{i=1}^{n} \left(w_{ij} a_i + b_j\right) \quad (1)$$

n is the input data I = 0,1,2, 3 …...,n, wij denotes interconnection weights of the input data ai, or bj denotes bias for neuron. Information is saved as a collection of connection biases and weights. A transfer function F is used to process the sum of weighted inputs with bias, and Eq. (2) provides output:

$$Y = F(X) = F\left[\sum_{i=1}^{n} w_{ij} a_i + b_j\right] \quad (2)$$

In general, hidden or output layers have a linear or non-linear activation function or transfer function. To establish the connections between the inputs and outputs, a variety of learning methods are available. The FFBP learning techniques are most commonly utilized. The sigmoidal function, whose output is among 0 or 1, a commonly used nonlinear activation function, and s sigmoid transmission function is shown by:

$$F(X) = \frac{1}{1 + e^{-x}} \quad (3)$$

Once negative values are discovered in the input or output layer, tansig transfer function is employed, which defined:

$$F(X) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (4)$$

Training of model is done with a certain number of neurons in the transfer function, a momentum factor, and a learning rate. The greatest popular type of neural network for predicting solar collector system performance is the MLFFNN.

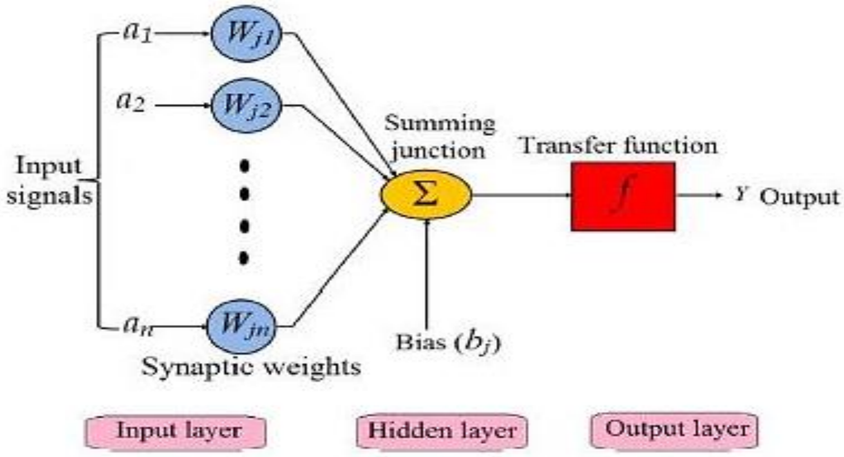

Fig.7. MLFNN model

4.3. Radial basis function (RBF)

There are three levels in the RBF model: input layer, output layer and hidden layer. Fig.8 shows RBF model's fundamental architecture, which is comparable to 3 layers of the MLFFNN model. Feed forward neural networks are used in both models. The signals are gathered at the input layer and transmitted through 2nd layer, that is the hidden layer, in the RBF model. The situation passes via the output layer after dispensation in the hidden layer, which creates output data.

while linear purpose is utilized at the output layer. In hidden layer, the handover function is usually a Gaussian function, define in Eq. (5):

$$a_j(x) = exp\left(-\frac{\|x_i - c_j\|^2}{2{\sigma_j}^2}\right) \quad (5)$$

x_i or c_j are input center of the RBF unit, while j is width of j^{th} neuron. The output of j^{th} RBF unit is denoted by a_j in Eq. (5). Eq. (6) describes Production layer's operation is linear:

$$y_k\,(x) = \sum_{j=1}^{n} w_{jk} a_j(x) + b_k \quad (6)$$

w_{jk} is the connection weight among k^{th} output unit, y_k is the k^{th} output unit for the input vector x, b_k is bias connection between j^{th} hidden layer unit and k^{th} output unit, j^{th} hidden layer.

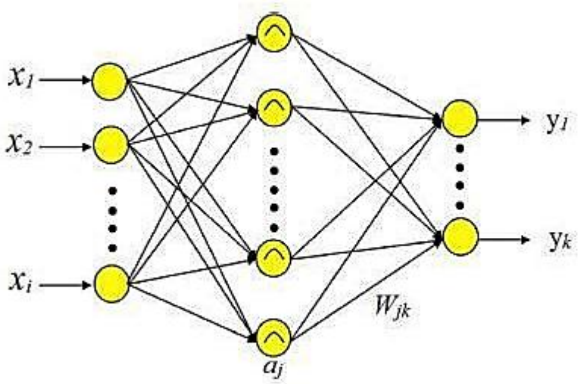

Fig.8. RBF model

4.4. Extreme learning machine (ELM)

Zhu et al. [85] presented the ELM for single-layer feed-forward neural network (SLFN) structure in 2006. It is founded on premise that every continuous function in the problem space may be approximated by random input weights and biases [86]. Because of this assumption, the SLFN weights may be computed using mathematical theories and the issue does not require an iterative procedure. As a result, the ELM delivers a lightning fast SLFN training method. ELM also methodically calculates all network variables, avoiding needless human involvement.

ELM involves a three-step procedure: 1. SLFN is generated; 2. the SLFN's weights or biases are set at random; 3. the hidden layer weights output are designed by inverting hidden layer output matrix [87].

SLFN with L hidden nodes may be theoretically constructed for a dataset comprising N training samples with m-dimensional target vectors and n-dimensional input vectors:

$$\sum_{i=1}^{L} \beta_i G(w_i x_j + b_j) = o_j \quad j = 1,2,3,\ldots\ldots,N \quad (7)$$

w_i is weight vector, x_j is input vector, G is activation function, β_i is weight vector connecting i^{th} hidden neuron to output neuron, b_j is bias vector and o_j is output vector.

4.5. General regression neural network (GRNN)

Specht was the first to apply the GRNN method [88]. The kernel regression network-based RBF architecture is known as GRNN. This method does not require an iterative strategy to mimic effects such as back propagation methods. It has the ability to estimate any arbitrary equation between the input and the output vectors on its own. A probabilistic model connecting independent (Input) and dependent (Output) variables are used in the generalized regression neural network (GRNN) method. The basic diagram of the GRNN is shown in Fig.9.

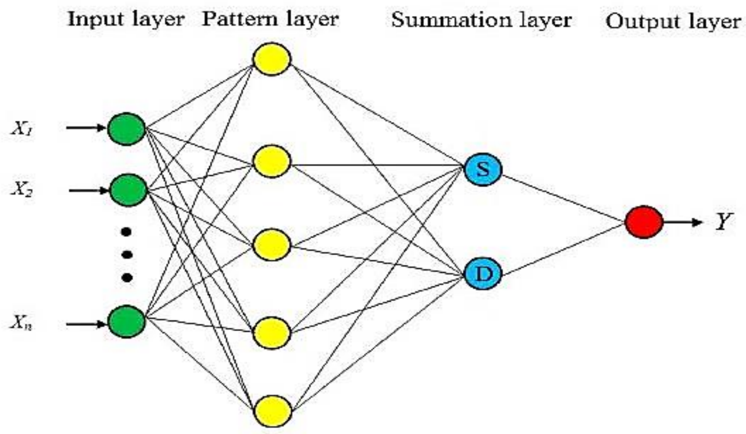

Fig.9. GRNN model

5. Result and Discussion

5.1. Model performance indicators

A desired AI model is one that is not just as basic as feasible but also incorporates relevant data. While include all possible input variables in a model improve the model's performance, it also increases the complexity and training time of the model. Furthermore, AI models may often produce satisfactory results with fewer input variables. Several approaches for determining the most influential subset of input factors have been suggested in the literature.

The training and testing phases of AI models are used to assess their performance. 70 percent of data was casually allocated to training phase while remaining 30% was allocated to testing phase [24]. The RMSE was used to measure models' performance. The 4 models like ELM, ANFIS, RBF and MLFNN are being tested and trained to evaluate the RMSE value. The inputs for TA are shown in table 6.

Table: 6 Input variables

Inputs	**Name**	**Maximum**	**Average**	**Minimum**
Input 1	Slip (mm)	11	3.80	0
Input 2	Length (mm)	100	55.62	50
Input 3	Inclination (deg)	134	120.3	113.5
Input 4	Height (mm)	100	74.3	62
Input 5	Width (mm)	100	74.3	60

5.2. Graph's analysis

The models evaluated the RMSE value by the testing and training. Table 7 shows the RMSE value of each model. Fig.10 shows the RMSE of models with testing and training [24]. The 4 models predict the TA at different points.

Table: 7 RMSE value of each model

Models	RMSE value	
	Training	Testing
ELM	31.60	30.02
RBF	30.90	31.34
ANFIS	31.31	31.96
MLFNN	30.6	31.20

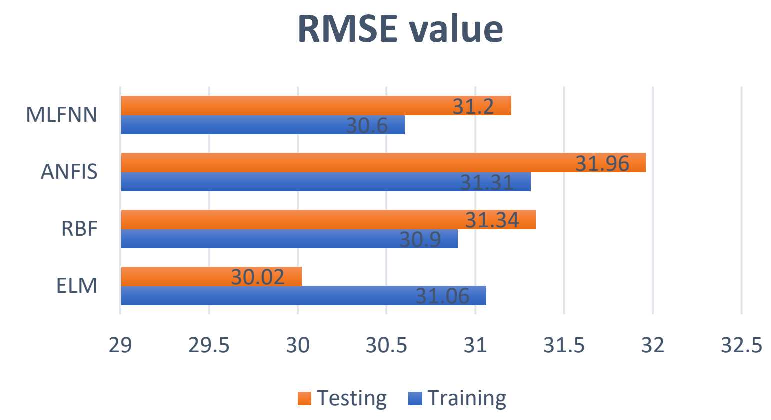

Fig.10. RMSE value

6. Suggestion for future search

In future, the TA can be optimized by other ANN models or Machine learning models. Based on a study of the aforementioned literature, it has been determined that the following issues remain unexplored and can be pursued in future research in the field of ANN techniques.

- Prediction of SC system performance utilizing several ANN models like RBF, GRNN, MLP, NARX, and PNN,
- As well as compared the performance of all models. Additionally, to choose best neural model for reliable outcomes. Purpose of the best ANN model utilizing multiple input variables and varied settings.
- A comparison of several ANN learning technique based on the solar collector act forecasts in order to choose the best learning algorithm based on the findings.
- To determine the number of neurons in hidden layer of an ANN model using various relations given by various researchers, to accurately anticipate the outcomes.
- Hybridization of the ANN technique with the other computing methods to predict system performance.
- The results of the ANN model are compared to that of PSO, SVM, MLR, GA, and ANFIS, among several other soft computing methods.
- Using the PSO or SA approaches to improve ANN structure for solar collector performance prediction.
- To optimize the ANN structure using an ANT colony method. Using an ANN model, analyse the energetic performance of a solar air/liquid collector.
- To forecast heat transfer or fluid movement of various solar air collectors.

7. Conclusion

The key to tilt angle design requirements for SWH are covered in detail in this article. Similarly, the research has allowed for a comparison of several techniques that were utilized to get the output of the best solar system. The employment of tilt angles in a variety of applications is discussed. Solar systems that used the ideal yearly tilt angle showed a considerable gain, however tracking systems were not suggested since there is a maintenance leakage in developing countries. The main objective of this work is to examine SWH performance at various tilt degrees, develop an ANN model for TA optimization, and evaluate the effects of various ANN models. The prior study looked at TA radiation on an hourly, monthly, and year basis. The TA applications like optimization by ANN models, optimization of TA with other models and optimization of TA by PSO, GA, SA have been discussed in this article. Theoretical principles and calculations were put to the test in a number of different solar systems, each with its own set of variables. For the purpose of TA optimization, the four ANN models are compared. The RMSE value by testing and training of models is carried out and then compared the models. In comparison to other models, ELM provides higher performance and requires less time. Most researchers use fundamental equations and model simulations to conduct sufficient tilt angle research. The future scope with other different models has been stated in this article.

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