
Harnessing Solar Energy: A Comprehensive Review of Solar Thermal Collector Applications

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Abstract

This study examines the importance of efficient solar collector design for optimal performance in low to medium-temperature applications, emphasizing the role of Artificial Neural Networks (ANN) in enhancing system efficiency. ANN, known for its speed and accuracy in solving complex problems, is widely used across various fields such as science, engineering, and business. The primary aim is to review ANN applications in predicting solar collector performance and to identify future research gaps. The systematic literature review (SLR) and meta-analysis focus on ANN applications in solar thermal collectors, covering research from 2000 to 2021. Out of 374 initial papers, 86 utilized ANN methods. The review analyzes data collection methods, ANN model setups, evaluation metrics, and meta-analysis results. Findings indicate that most studies focus on solar water heaters (SWH) using water as the heat exchanger, with a significant concentration of research conducted in Asia. The Multilayer Perceptron (MLP) model is predominantly used, appearing in 76 of the 86 reviewed papers. A key research gap is identified in the limited use of deep learning and other traditional machine learning models, as well as the underrepresentation of African data in ANN modeling for solar thermal devices. Despite covering two decades of studies, there is an observed exponential growth in research interest, highlighting the need for future studies to incorporate a broader range of machine learning algorithms for comprehensive conclusions.

Keywords: Solar Water Heater, Artificial Neural Networks, Multilayer Perceptron, Solar Collector.

1. Introduction

The current global energy situation illustrates that most countries worldwide depend on fossil fuels (oil, gas, and coal) to meet their needs. Overexploitation of the primary energy sources has caused the depletion of fossil fuels, and there will only be 119 years of coal production, 46 years of oil production, and 63 years of natural gas flow left in the ground with the current proven reserves(Z. Wang et al., 2015). The global economy is mainly based on fossil fuels, which produce electricity, heat, chemicals, fuels, and energy. In the total primary energy supply, fossil fuels account for 81 %(Chemical et al., 2021) , and their consumption has led to an increased concentration of greenhouse gases (GHG), causing global warming and leading to climate change. To respond to the sustainable development goals (SDG) **7** (Chirambo, 2018) and **13** (Bruce M et al., 2018), energy resources conservation has become a priority on the planetary scale and has pushed researchers to find new suitable techniques by exploiting renewable energies (Series & Science, 2021) such as solar energy, hydropower, wind power, geothermal energy, biomass energy, and new hydrogen energy (Ekanayake & Limmeechokchai, 2020). Therefore, the massive solar energy production from the sun has many applications due to their innumerable economic and environmental interests. Where many solar collectors can be used to exploit the sun's energy either thermally or as photovoltaic, as needed (Said et al., 2021). Solar energy is the most important source of renewable energy because it represents a clean, unlimited, and environmentally friendly energy source. The two common types of devices utilizing solar energy are the direct conversion of solar energy to electrical energy by photovoltaic (PV) cells (Sontake et al., 2020) and the direct conversion of solar energy to heat energy (solar thermal) using solar thermal collectors. The total amount of solar radiation reaching the Earth is about 1.73 × 1017 W. Not all solar radiation that enters the Earth's atmosphere reaches its surface. About 30% of the solar radiation is reflected back into the atmosphere, and almost 20% of it is absorbed by clouds and air. Nearly three-fourths of the Earth is water. Only 0.1% of total solar radiation can heat the Earth (Esmaeil et al., 2017). The solar collector is the main component of the solar thermal system. It absorbs solar radiation and transfers heat to the working fluid. To augment the performance of solar thermal collectors, experimental, analytical and computational techniques are implemented, which require a lot of time to arrive at an accurate result (Ghritlahre & Prasad, 2018d). Theoretical-based results, on the other hand, are suitable only for simplified models of the practical devices under many simplifying assumptions (Elsheikh et al., 2019). Due to its simplicity, high speed and capability to solve complex and nonlinear relationship among the variables and extracted data, Artificial Neural Networks (ANNs) (Ghritlahre & Prasad, 2018c) (Elsheikh et al., 2019) are therefore becoming the best choice of approach and many other thermal systems. ANN is a powerful data-driven, self-adaptive, flexible computational tool capable of handling large amounts of data sets. Additionally, this technique is found very suitable for implicitly detecting complex non-linear relationships between dependent and independent variables with high accuracy (Ahmadi et al., 2020).

Table 1: Research questions posed for the Systematic Literature Review

RQ#	Research Question	Theme
1	Which solar thermal device and location of experimental data were used for the study?	Data collection
2	Which Artificial neural network models, independent variables and dependent variables are widely employed in performance evaluation of solar thermal collectors	solution modelling
3	Which metrics are used to evaluate the performance of neural networks for performance modelling and evaluation of solar thermal collectors	solution modelling

The main aim of this study is to conduct a systematic literature review (SLR) on ANN application in solar thermal collector performance. This will provide an understanding and summary of the current state of the art within the field, as well as highlighting limitations and open challenges for future research.

More specifically, the study aims to investigate a comprehensive investigation to elaborate:

1. The solar-thermal device is considered, and data sources and predictors are measured to model the performance of solar thermal collectors.

2. The type of artificial neural network models exploited by the researchers.

3. the evaluation metrics used by researchers for the exploited models.

Moreover, a meta-analysis of the performance of the defined machine learning models is finally presented. To this aim, the research questions in table1, are set up to guide the research journey. Apart from the general analysis made, limitations in neural network models based on the choice of data set, location of the dataset, and type of models adopted are also highlighted.

1.1 RELATED RESEARCH

In actual fact, no *detailed* Systematic Literature Review with meta-analysis has been conducted with the aim of understanding and summarizing the research on artificial neural network applications on the performance evaluation of solar thermal collectors. However, it is important to point out that some secondary studies on the field have been proposed.

The work presented (Mosavi et al., 2019) identifies 10 major ML models frequently used in energy systems, i.e., ANN, MLP, ELM, SVM, WNN, ANFIS, decision trees, deep learning, ensembles, and advanced hybrid ML models. The notable manuscripts are accordingly categorized into the relevant groups and further reviewed. The heat energy system is therefore explored by (Mohanraj et al., 2015) an ANN application on heat exchanger performance modeling.

In the field of solar device modeling, (Elsheikh et al., 2019) I made a further review of solar energy system modeling by focusing on ANN application only. With a brief discussion about the types of ANNs (MLP, Wavelet NN, RBF, and ENN), the effect of activation functions explored by the researchers was also reviewed in detail to determine their applications in different solar devices.

The idea of solar thermal modeling and performance evaluation was reviewed (Ghritlahre & Prasad, 2018c). In their review work, they summarized the state of the art in the said field by providing brief bibliometrics and technical analysis of the aim of the study, structure of neural networks used (i.e. neural structure), type of neural network and learning algorithm implemented for the study. Their study reveals the MLP as the most widely used model for the modeling and performance evaluation of solar thermal collectors.

The work aims to discuss (i) ANN, its types, its field, and the methodology of implementation and usage in different solar thermal applications. (ii) Different standard statistical performance evaluation criteria were used in the evaluation of ANN performance. (iii) ANN is applied in various solar thermal systems like solar collectors, solar air and water heaters, photovoltaic/thermal (PV/T) systems, solar dryers, solar stills, and solar cookers.

A detailed focus on solar air heater performance modeling is also exhausted in the review work by (Ghritlahre & Verma, 2021) and (Ghritlahre et al., 2021).

Table 2: Summary of related works from 1998 to 2018

Reference	**Period of review**	**Number of articles reviewed**	**PRISMA Method**	**Meta-analysis**
(Ghritlahre & Prasad, 2018a)	1998 – 2017	32	No	No
(Ahmad, Kumar Ghritlahre, et al., 2020a)	1999 – 2018	25	No	No
(Mohanraj et al., 2015)	1996 - 2014	121	No	No
(Ghritlahre & Verma, 2021a)	2009 – 2018	18	No	No
(Elsheikh et al., 2019b)	1998 – 2018	56	No	No
(Mosavi et al., 2019)	2013 – 2018	70	Partial	No
(Ghritlahre et al., 2019)	1998 – 2018	37	No	No

As shown in Table 2, though critical studies are done in the related review works, there exist a few literature gaps to be accomplished in future works. It was noticed that ANNs have gone far in the study of performance analysis of solar thermal collectors. In the related works, comprehensive studies were done to report study parameters and methods by a pool of researchers spanning periods of fifteen years and above. Though the minimum and maximum number of articles reviewed were 18 and 121, respectively, those reviews lack meta-analysis which provides a clear statistical evaluation of the empirical studies reviewed. In addition, laid down methods for systematic literature review like the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)(Appiahene et al., 2018)(Kamioka, 2019) were not followed.

Though numerous studies have been conducted on the application of ANN on solar thermal collectors, there is a need to conduct a systematic literature review and meta-analysis to establish a combination of numerical results from previous studies. This will help estimate descriptive statistics (Hedges 1987, Rosenthal 1978) and explain inconsistencies as well as the discovery of moderators and mediators in bodies of research findings(Rosenthal & Dimatteo, 2000).

1.2 CONTRIBUTION

The contributions made by this SLR are the following:

1. A set of 86 primary studies that proposed solar thermal collector performance evaluation prediction models. The research community can, therefore, utilize this study as a starting point to extend the knowledge on the stipulated topic.

2. A comprehensive synthesis of the primary studies identified. This includes four main themes:

(i) Solar thermal devices considered concerning data source and performance predictors,

(ii) artificial neural network model or approaches,

(iii) Design the evaluation strategies and performance analysis.

3. Future directions and recommendations based on the findings to support further research in the area are also provided.

The rest of the paper is organized as follows:

Section I presents the introduction, problem statement, research questions, objectives, literature review, and contribution of the work. Section II presents the methodology followed in achieving the specified objectives based on the research questions. Section III presents the results of the study. Section IV presents a discussion of the results attained and finally, the conclusion shows the conclusion aspect of the study.

2. Research Methodology

A systematic literature review has been used as a research methodology in this study as it is a defined and methodical way of identifying, assessing, and analyzing published literature to investigate a specific research question or phenomenon (Tallant, 1987). As done by other researchers in the field of software engineering (Azeem et al., 2019), SLR guidelines proposed by Kitchenham and Charters (Tallant, 1987) were adopted. The method adopted to accomplish the task was the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA).

2.1 SEARCH PROCESS OVERVIEW

A search strategy to collect all the available published literature relevant to the topic at hand was devised. The search strategy consists of search terms identification, resources to be searched, search process, and article selection (inclusion and exclusion) criteria adopted for the studies. In the primary search, the following search engines were used: Google Scholar, Connected Papers, Harzing Publish, and *Perish*. Based on population, intervention, and outcome (Santos et al., 2007), a search strategy for deriving the major terms was established. Here, the population is comprised of all solar thermal devices, and the intervention relates to the use of deep learning (neural network), while the outcome relates to the evaluation metrics used in the empirical studies. Searching from the year 2000 to 2021, special keywords were modeled with their corresponding alternatives

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(synonyms) in order to achieve a comprehensive search from individual resources. The following resources were searched by the search engines: Elsevier, MDPI, Taylor and Francis, Science Direct, Springer, ASCE, ASME, IEEE Conference, and other manual resources through snowballing(Wohlin, 2014). The selection of these databases was driven by the researchers' willingness to gather as many papers as possible to conduct the systematic literature review properly. Following the PRISMA(Kamioka, 2019) method, relevant identification, screening, exclusion, and inclusion criteria were implemented for the papers. As shown in Table 3, the final number of articles included in the meta-analysis was 86.

2.2 INCLUSION AND EXCLUSION CRITERIA

As shown in Figure 1, the initial search with the help of the aforementioned search engines resulted in a total of 329 articles that perfectly matched the said field of study. In addition to this, a snowballing technique was adopted to search other sources, which contributed to a total of 57 articles with the duplication of 12 articles. After identifying and filtering out the duplicated articles, a total of 374 articles were obtained after the screening. Though the screened articles fit into the study, about 9 of them fell beyond the date scope of the study and were excluded from the list. This resulted in a final list of 365 articles. To further articulate the inclusion, two restrictions were imposed to further exclude 279 articles. That is, 181 articles were out of the methodological scope and 98 with insufficient details that could help in the study.

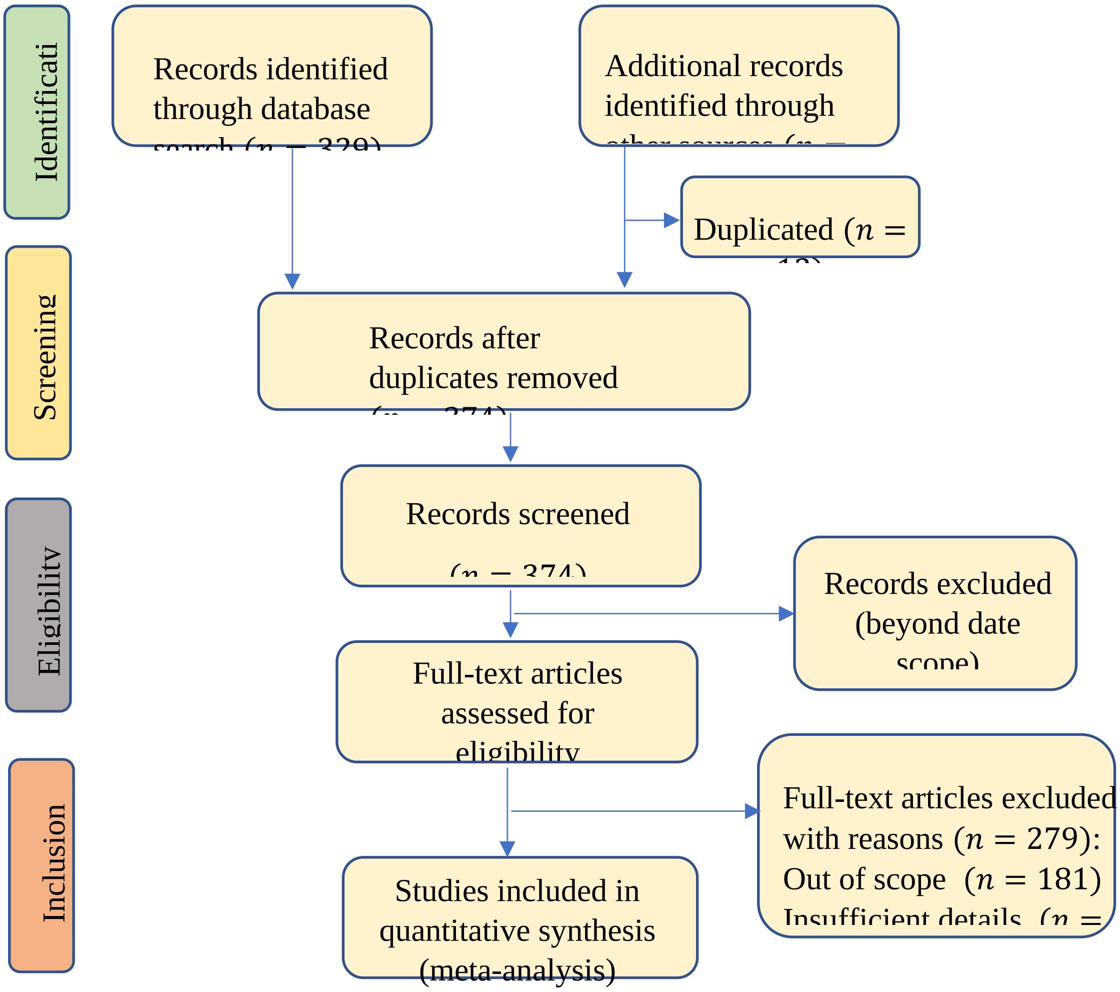


Figure1: Article selection process

2.3 DATA EXTRACTION

Once the final papers were selected to be used for the SLR, we proceeded with the extraction of the data needed to answer the research questions. Specifically, we relied on the data extraction form presented in Appendix 1 (ie. Table 6). Here, three categories of data were extracted: reference, methodology and evaluation metrics. The reference information comprised Author, date, case study (type of solar thermal device), resource, and publisher. The methodology comprised, Datapoints , Data Location, accumulation period, neural network algorithm adopted, input (predictor) variables and output variables.

Table 3: Resources searched and search results

Resource Name	Total Results Found	Initial Selection	Final Selection
Elsevier	214	125	42
MDPI	20	6	4
Taylor and Francis	28	13	7
Science Direct	16	7	3
Springer	24	5	3
ASCE	6	2	1
ASME	10	3	1
IEEE Conference	11	2	4
Others	57	31	21
TOTAL	**386**	**194**	**86**

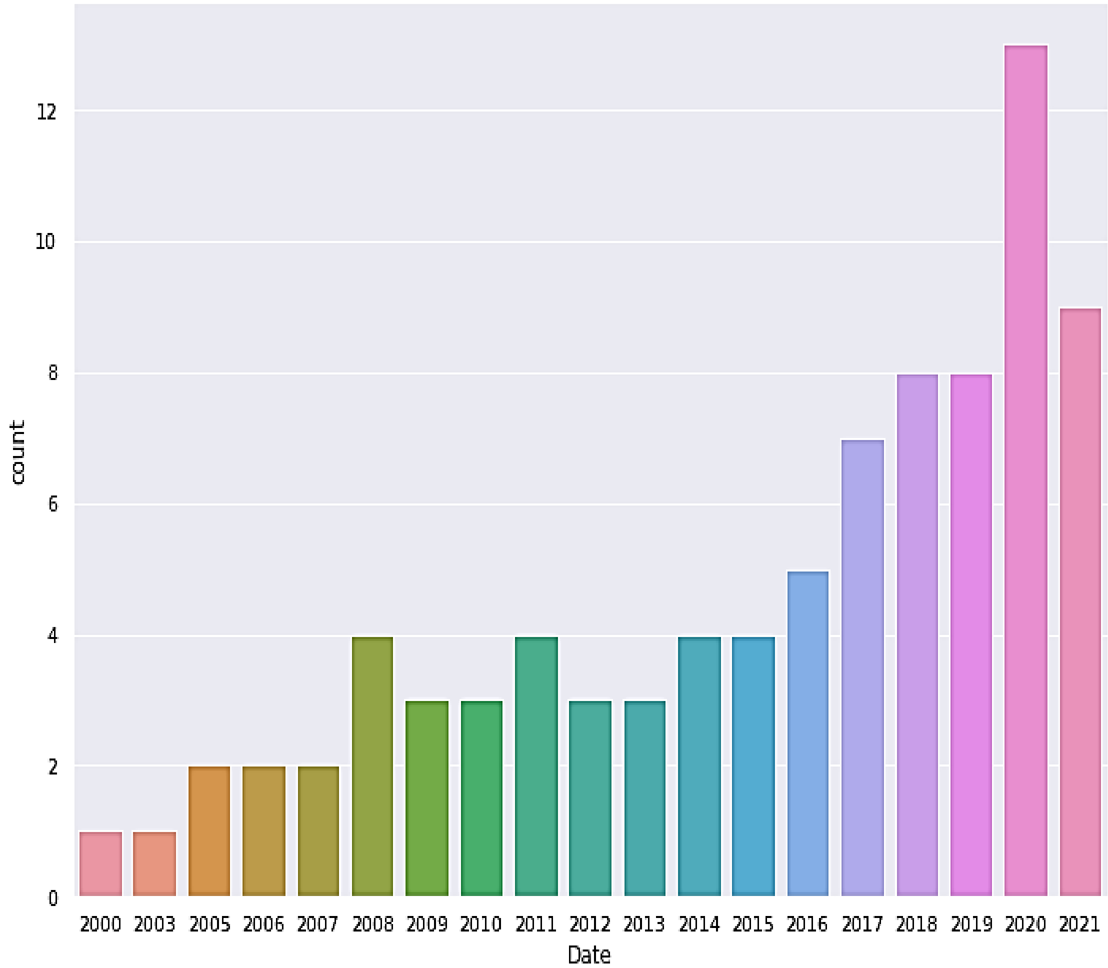
3. Results

Before reporting the results of the SLR with respect to the considered research questions, we provide a brief overview of the demographics of the papers that passed the inclusion criteria and the quality assessment.

3.1 DEMOGRAPHICS

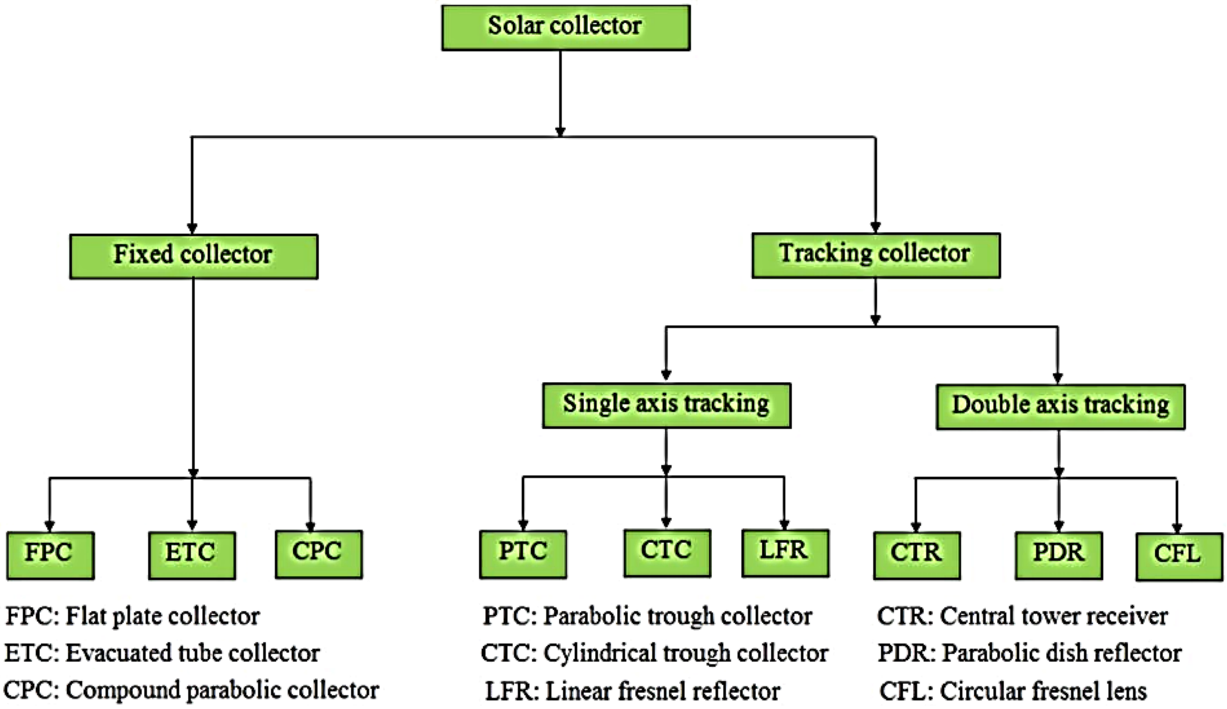
Table 4 demonstrates the final list of relevant primary studies that were analyzed in this SLR: References column highlights the Year, Publisher, Author(s), Resource, and Case study of the study. The methodology column shows the data points, location of data, accumulation period, deep learning algorithm adopted, input (independent) variables, and output (predicted) variables.

By observation from Figure 2, all the considered papers were published between 2000 and 2021; 58.14% of these primary studies were published after 2016 (i.e. within the upper-quartile of the period), possibly highlighting a growing trend that is now in the process of becoming a more established discipline. Moreover, it was observed that 75.58% of the primary studies were published in conference proceedings and international journals with the rest being taken from non-scopus-based journals.



3.2 DATA COLLECTION (RQ.1)

A solar collector is a device that collects the solar radiation incidents on it, converts it into thermal energy, and transfers this energy to a working fluid (gas or liquid). A higher efficiency and better performance also increase the costs of the collector. From the study conducted, it was found that an important parameter to track the performance and effectiveness of a solar collector is the thermal efficiency(Du, Lund, Wang, et al., 2021) which is defined as the ratio of the useful thermal energy gain to the incident solar flux on the tube. This factor can sometimes be interpreted using *Nusselt Number* (Ghritlahre & Prasad, 2018d) and is driven by the outlet temperature of the fluid used as the heat exchanger. Thermal efficiency is also a key factor for any optimization or performance enhancement effort. The types of solar collectors are shown in Figure 3. Solar collectors are broadly classified into two categories, such as fixed collectors and tracking collectors. The fixed collectors are kept at rest, whereas tracking collectors track as per the movement of the sun such that the incoming solar radiations always incident perpendicular to them. The tracking solar collectors are subdivided into two categories: single and double-axis tracking.



collector. The single-axis tracking collector is categorized into three types such as parabolic trough collector, cylindrical trough collector, and linear fresnel reflector. Again, the double-axis tracking collector is sub-categorized as a central tower receiver, parabolic dish reflector, and circular fresnel lens. These solar collectors have their applications depending upon the feasibility and quantity of energy required.

The instantaneous performance of a solar collector under specific conditions of climatology and operation is determined from the energy absorbed and lost in the tests carried out on the solar collectors (Hottel and Woertz, 1942; Hottel and Whillier, 1955; Bliss, 1959; Duffie and Beckman, 2013), where performance is measured in an appropriate time interval (Diez et al., 2019).

The useful energy of the solar collector at a given moment of time results from the difference between the energy absorbed and the outside energy lost, by Eq. (1)

$$Q_u = F_R A[G(\tau\alpha) - U_L(T_{in} - T_a)] \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (1)$$

Where Q_u is the useful power drawn from the solar collector (W); F_R is the heat extraction efficiency factor of the solar collector; A is the area of the solar collector (m^2) exposed to sun radiation; G is the solar irradiance that affects the solar collector per unit area (W/m^2); τ is the solar transmittance of the transparent cover; α is the absorptance of the solar collector plate; U_L is the global coefficient of energy losses of the solar collector ($W/(^0Cm^2)$); T_{in} is the temperature of the working fluid at the solar collector inlet (^0C); T_a is the ambient temperature in (^0C).

The useful energy could also be calculated using the working fluid that circulates in the solar collector, by the equation (2):

$$Q_u = A\dot{m}c_p(T_{out} - T_{in}) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (2)$$

Where $\dot{m}$ is the mass flow of the working fluid per unit area of the solar collector ($kg/(sm^2)$); c_p is the specific heat of the working fluid ($J/(^0Ckg)$); T_{out} is the temperature of the working fluid at the solar collector outlet (^0C).

The results of solar collector tests are offered in terms of performance η, such as equation (3).

$$\eta = \frac{Q_u}{GA} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (3)$$

3.2.1 SOLAR-THERMAL DEVICE

For the vast number of applications considered by the researchers, the working fluid for heat exchange is, air, water, or Nano-fluid. Nano-fluid can be made of mineral (thermic) oil (W. Wang et al., 2017) (Boukelia et al., 2017a) or other compounds like CuO-water, Al_2O_3(Mirzaei & Mohiabadi, 2021) and TiO_2(Salih et al., 2021). Figure 4 shows clearly that, about 60 percent of the studies used water as the heat transfer medium, 30 percent used air about 13 percent of studies focused on Nano-fluids.

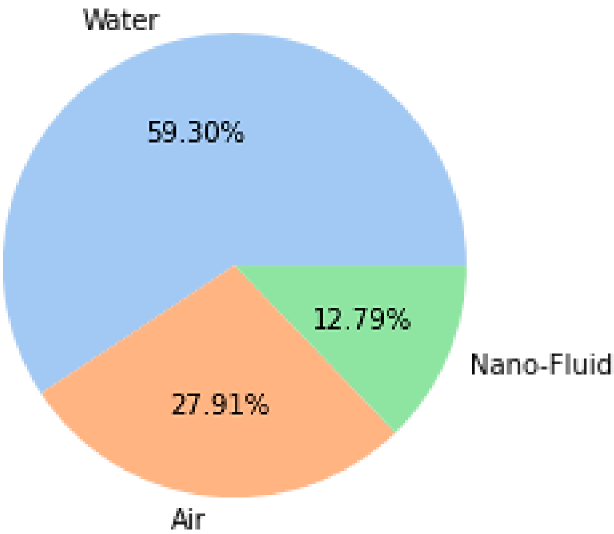


Figure 4: Working fluid used in empirical studies

3.2.2 EXPERIMENTAL LOCATION

The amount of light intensity received by the surface of the panel is determined by the direction and tilt of the photoelectric panels(Asma et al., 2019). When placing the solar panels in the northern hemisphere, they should be directed for the south side and they must also face the northern side of the southern hemisphere. In areas close to the equator, the orientation is not significant but at least 10 degrees inclination is necessary to discharge rainwater. The location (Yohanis et al., 2006) of the solar device is therefore a crucial parameter to its performance evaluation. As shown in Table 4, about 66 percent (57 out of 86) of the study, focuses on Asia. Though the data source (location) of about 10 percent of the study was not stated clearly, it shows clearly that about 2 percent of the study was done in Africa.

Table 4: Continental location for data collection (experimentation)

Dataset Location	Number
Asia	57
Europe	8
Africa	2
South America	4

Australia	1
North America	3
Synthetic	2
None	9

3.3 SOLUTION MODELLING (RQ.2)

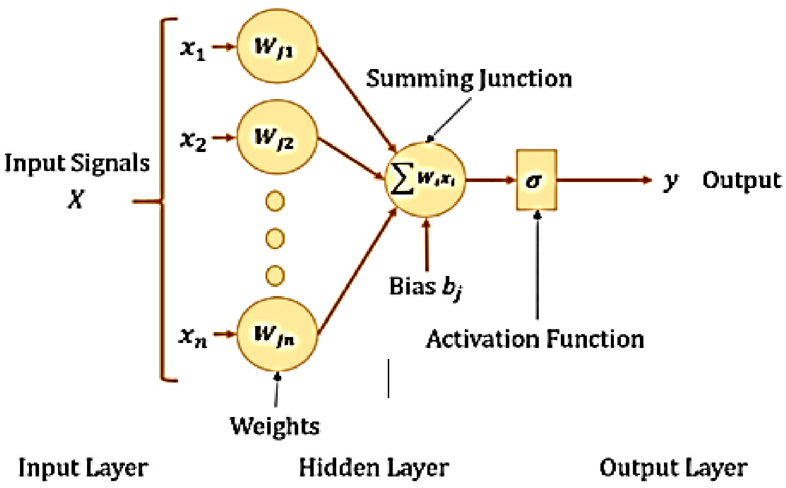
The second research question of the SLR was related to the methodology adopted by researchers to undertake their individual empirical studies. This involves the following:

- The type of Artificial neural network adopted
- Independent variables are used as predictor variables for the ANN models and finally,
- The output or dependent variable being evaluated

3.3.1 ARTIFICIAL NEURAL NETWORK MODELS

Artificial neural networks are a common technique used in machine learning for supervised classification and regression tasks (ie. The desired outputs are known beforehand and thus can be compared with the network's predictions). ANN functions work like the human brain in two ways (Ahmad et al., 2020): learning and storing information that is called weights in interconnected connections. The neuron collects multiple inputs in combination with attachment weights from other neurons performs a nonlinear activation process and generates a single output data that can go to the other neurons. Such input data is analyzed by the neurons and transferred to the next network layer. ANN is defined as sequential linear regressions evaluated by non-linear functions. Each regression is called a hidden layer and the number of outputs of each regression in each regression is in a hidden unit. These are represented by a set of matrices and vectors (weights W and biases b) as the transitions between the input, hidden, and output layers of a network, as shown in Figure 2. This relationship can also be seen in equation 4, in which the output of an intermediate layer y_p is calculated by applying a non-linear transfer function σ to a pondered sum obtained from the input data X and the network's trainable parameters (W,b). Usually, a linear activation function is used for the output layer of the network to calculate the regression result of each node.

$$y_p = \sigma(W^T X + b) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

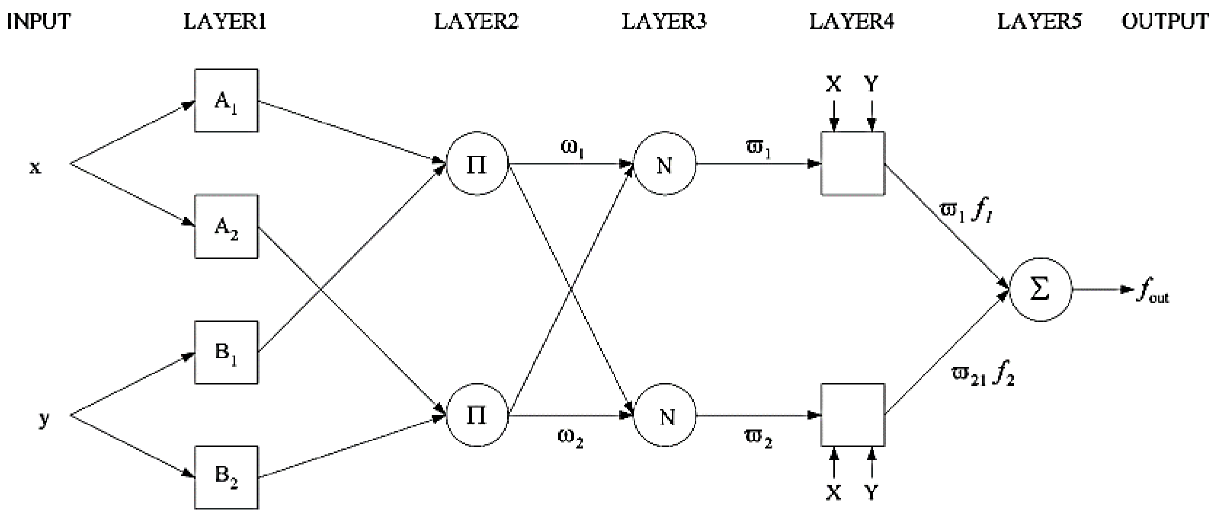


Some of the commonly used activation functions are sigmoid, hyperbolic tangent, softmax, rectified linear unit (ReLU), leaky ReLU, etc. The training process is usually done by propagating errors from the output to the input layers, and adjusting the weights and biases within each layer to correctly represent the given data. This is known as backpropagation, by which these parameters are adjusted by chain rule and gradient descent techniques (Correa-Jullian et al., 2020). Depth is added to the basic ANN network by stacking several hidden layers, known as Multi-Layered Perceptron (MLP) where consecutive non-linear mathematical operations are applied to each layer. For an MLP (also known as Deep Neural Networks or DNN), the input of each hidden layer is the output value of the previous one, and equation (4) is rewritten as:

$$h_i = \sigma(h_{i-1}^T W_i + b_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (5)$$

3.3.2 ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) METHOD

ANFIS is an artificial neural network and relies on the Takagi-Sugeno fuzzy inference system. This method benefits from the advantage of both fuzzy and neural networks. ANFIS is a hybrid model that combines the ANN adaptive capability and the fuzzy logic qualitative approach. By utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way humans process information, ANFIS harnesses the power of the two paradigms: ANNs and fuzzy logics, and overcomes their own shortcomings simultaneously(Çaydaş et al., 2009). The inference in ANFIS is based on a set of fuzzy rules for finding the nonlinear functions with learning ability. There are five layers in ANFIS. In the first layer, called the fuzzification layer, the input data is given and the membership functions and degrees can be assigned. The second layer, called the rule layer, generates the firing strengths of rules. The calculated strengths are then normalized in the third layer. In the fourth layer, the normalized input is given and the consequent parameters can be computed. Finally, the output of the fourth layer, the defuzzification values, is sent to the last layer to generate the output(Shafieian et al., 2020).



Convolutional Neural Network (CNN) is a class of deep feed-forward artificial neural networks that is commonly used in computer vision problems such as image classification. The distinction of CNN from a “plain” multilayer perceptron (MLP) network is its usage of convolutional layers, pooling, and non-linearities such as tanh, siдmoid, and ReLU(Agarap, 2017). The hidden layer of the convolutional neural network includes a convolution layer, pooling layer, and full connection layer. The structure of the CNN model is illustrated in Figure 7.

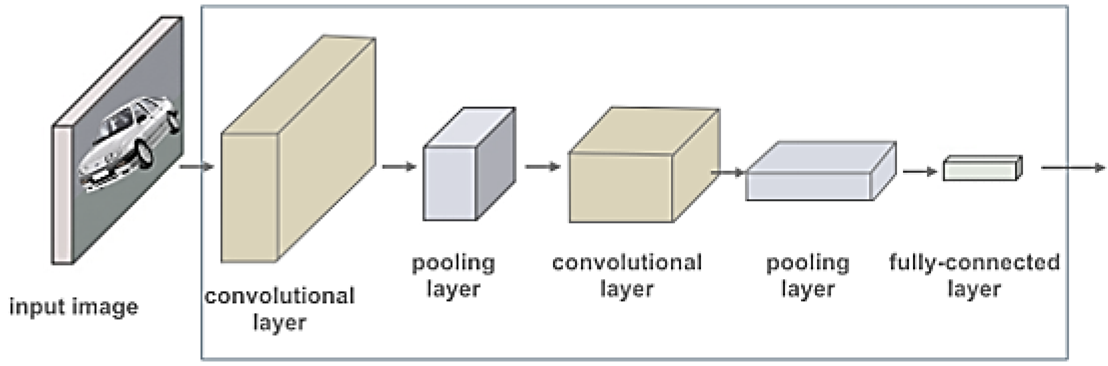


Figure 7: Block diagram of Convolutional Neural Network (CNN)

The convolution layer is in charge of the feature extraction of input data (Du, Lund, & Wang, 2021). It contains several convolution kernels. Each element of the convolution kernel corresponds to a weight coefficient kernel and a bias vector, which is similar to the neuron of a feedforward neural network. Each neuron in the convolution layer is connected with several neurons in the region close to each other in the previous layer. The size of the region depends on the size of the convolution kernel, also known as the “receptive field”. When the convolution kernel works, it will scan the input features regularly, multiply the input features in the receptive field, and add the deviation. Convolution layer parameters contain the convolution kernel size, step size, and filling. The larger the convolution kernel is, the more complex the extracted input features are. The convolution step size defines the distance between the positions of the convolution kernel when it scans the feature image twice. Filling is a method to increase the size of the feature image by convolution kernel to counteract the effect of size shrinkage before the feature graph passes through the convolution kernel. The convolution layer contains an activation function to help express complex features. After feature extraction in the convolution layer, the output feature map will be transferred to the pooling layer for feature selection and information filtering. The selection of the pooling area in the pooling layer is the same as that of convolution kernel scanning feature map, which is controlled by pool size, step size and filling. The fully connected layer is located in the last part of convolutional neural network and only transmits signals to other fully connected layers. The convolution layer and pooling layer in the convolutional neural network extract the features of the input data. The function of the fully connection layer is to nonlinear combine the features of the extracted features to get the output, that is, the fully connection layer tries to use the existing high-order features to complete the learning goal.

3.3.4 Recurrent Neural Network (RNN)

Recurrent neural network as shown in figure 8 is a natural generalization of the feedforward neural networks to sequences. Given a general input sequence $[x_1, x_2, \dots, x_k]$ where $x_i \in \mathbb{R}^d$ (different samples may have different sequence length k), at each time-step o RNN modeling, a hidden state is produced, resulting in a hidden sequence of $[h_1, h_2, \dots, h_k]$. The activation of the hidden state at time-step t is computed as a function f of the current input x_t and previously hidden state h_{t-1} as:

$$h_t = f(x_t\ h_{t-1}).$$

At each time-step, an optional output can be produced by $y_t = g(h_t)$, resulting in an output sequence $[y_1, y_2, \dots, y_k]$, which can be used for sequence-to-sequence task (Zhang et al., 2018).

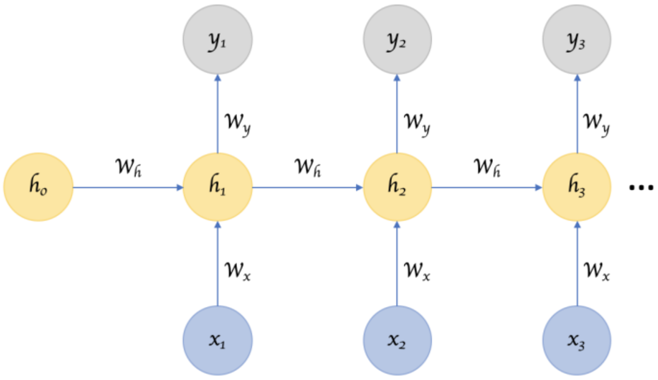


Figure 8: Basic structure of Recurrent Neural Network

3.3.4 LONG-SHORT TERM MEMORY (LSTM)

LSTM is built based on memory cells, which contain a recurrently self-connected linear unit, referred to as the Constant Error Carousel (CEC). CECs resolve the vanishing/exploding gradient problem as their local error backflow remains constant until the cell is exposed to new inputs or error signals. By introducing input and output gates, the CEC is protected from both forward-flowing activation and backward-flowing error. Besides, a third forget gate is used to control the amount of information to forget from the historical data. A typical structure of the LSTM unit is presented in Figure 8. In practice, LSTM is capable of learning and remembering long-term dependencies, which makes it suitable for time-series forecasting with long input sequences (Kisvari et al., 2021).

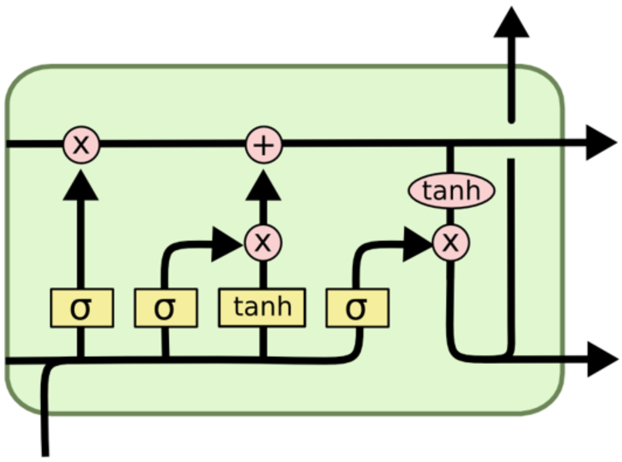


Figure 8: Basic structure of LSTM

3.3.5 GATED RECURRENT NEURAL NETWORKS

GRU was first proposed as a more compact and simpler to-implement hidden unit inspired by the LSTM unit. GRUs contain a reset and an update gate, which adaptively control how much each hidden unit remembers or forgets during training without having separate memory cells. This means each hidden unit is able to adaptively capture dependencies over different time scales, depending on the activity frequency of its gating mechanisms. For example, short-term dependencies will be captured via frequent reset gate activity, and long-term dependencies via frequent update gate activity (Kisvari et al., 2021). A classical structure of the GRU unit is presented in Figure 9.

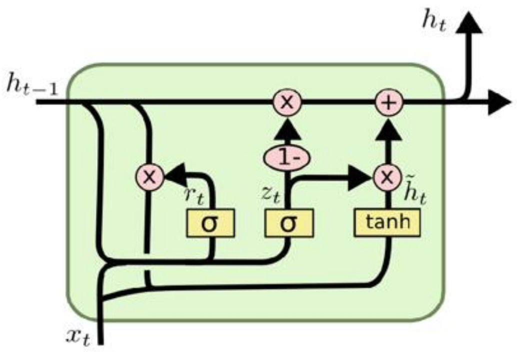


Figure 9: Basic structure of Gated Recurrent Unit cell

3.3.6 RADIAL BASIS FUNCTION NN

The Radial basis function neural network is a type of ANN with one input layer, one hidden layer, and one output layer(Thanh et al., 2016). The input layer is mapped on the hidden layer via the non-linear activated function or radial basis functions (known as neurons), whereas the connection from the hidden layer to the output layer performs a linear transformation. The input layer has $n_1$inputs by $x_1, x_2, \dots. x_{n1}$ and its vector from is represented by

$$X = [x_1, x_2, \dots . x_{n1}]^T \dots \dots \dots \dots \dots \dots \dots . . (6)$$

In the hidden layer, the multivariate Gaussian function is chosen as the activated function, and its formulation is shown as follows:

$$\varphi_i = esp\left(-\frac{\|X - C_i\|^2}{2\sigma_i^2}\right). i = 1,2, \dots\ n_3 \dots \dots \dots \dots \dots \dots \dots . . (7)$$

Where n_2 is the number of neurons in the hidden layer, $C_i = \left[C_{i1}, C_{i2}, \dots\ C_{in_1}\right]^T$. σ_i deonote the center of radial basis function and node variance (or width) of ith neuron, and $\|X - C_i\|$ is the norm value (euclidean distance) which is measured by the inputs and the node center at each neuron. Finally, the network output can be written as:

$$y_j = \sum_{i=1}^{n_2} w_{ji}\varphi_i,\ \ j = 1, 2, \dots, n_3 \dots \dots \dots \dots \dots \dots \dots \dots \dots (8)$$

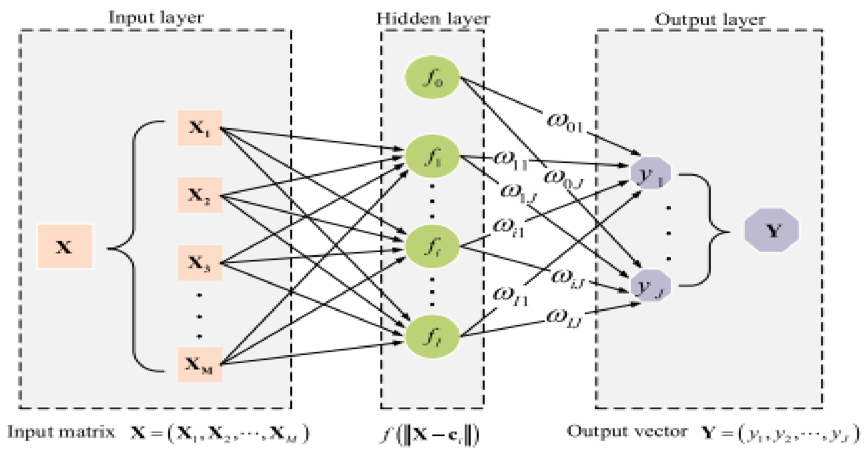


Figure 10: Radial basis function neural network

3.3.7 ELMAN NEURAL NETWORK

The Elman neural network (ENN) is a type of feedback neural network. The back propagation neural network consists of a unique feedback term called a hidden or processing layer in addition to the input and output layers. An input layer corresponds to the input signals, a hidden layer has a linear or nonlinear combination of the input signals as its transfer function, and an output layer is called a linear weight. In particular, a feedback output vector of the hidden layer neurons that feeds back to the input layers is called a context unit. It stores the output information from the neurons of the hidden layers in the previous time frame and keeps feeding back to the input layers. The machine learning sequence has an opportunity to learn from the inputs at different time stages (Cho et al., 2020). The basic architecture of the ENN is shown in Figure 11. There are m inputs, n feedback processing neurons, and k outputs, where $x(t)$ is a $m \times 1$ vector and $y(t)$ is the output of the hidden layer. In addition, $y(t)$ is not only an input of the output layers $y(t+1)$ but also an input of the input layers. $u(t+1)$, an input vector of $(x_m + h_{en})$, is obtained in light of the connection of $y(t)$ and $x(t+1)$. $u_i(t)$ can represent $u(t)$ on unit i. If unit i belongs to set A, $u_i(t)$ is equal to $x_i(t)$. This means that unit i belongs to set B, with $u_i(t)$ equal to $y_i(t)$ as defined in equation (9). The concept of the algorithm is defined by equation (9) – (13). $z_k(t+1)$ derived from the output layers is a nonlinear function of $net_k(t+1)$.

$$u_i(t) \begin{Bmatrix} x_i(t) \ if \ i \in A \\ y_i(t) \ if \ i \in B \end{Bmatrix} \dots\dots\dots\dots\dots\dots\dots\dots.(9)$$

$$net_j(t+1) = \sum\nolimits_{i \in AUB} W_{ji}(t) u_i(t) \dots\dots\dots\dots\dots\dots..(10)$$

$$y_i(t+1) = f\left(net_j(t+1)\right) \dots\dots\dots\dots\dots\dots\dots\dots.(11)$$

$$net_j(t+1) = \sum\nolimits_{i \in AUB} v_{ji}(t+1) y_j(t+1) \dots\dots\dots\dots\dots\dots..(12)$$

$$z_k(t+1) = f\big(net_k(t+1)\big) \dots\dots\dots\dots\dots\dots\dots\dots..(13)$$

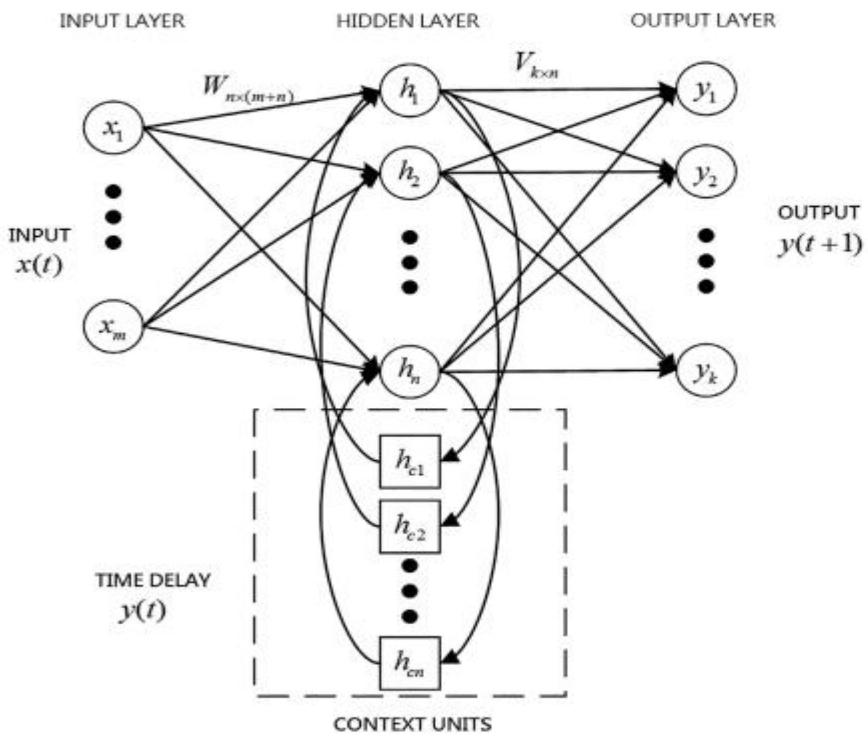


Figure 11: Elman Neural Network

3.3.8 NONLINEAR AUTOREGRESSIVE WITH EXOGENOUS INPUT (NARX) ANN

A time series is a sequential set of data points, measured typically over successive points in time spaced at uniform time intervals. It is mathematically defined as a set of vectors $y(t)$, $t = 0, 1, 2, \dots, d$ where t represents the time elapsed with a set of discrete values$y_1, y_2, y_3, \dots, etc$. The variable $y(t)$ is treated as a random variable and the measurements taken during an event in a time series are arranged in a proper chronological order(Raptodimos & Lazakis, 2020).

In the NARX model, uture values of a time series $y(t)$ are predicted from past values of $y(t)$ and another external series $x(t)$. Although the NARX network is applied for short-term forecasting, multi-step-ahead predictions can be acquired if knowledge of the future exogenous inputs is known. This is done by using the output of a one-step-ahead prediction as the input for the subsequent prediction in an iterative process. Data are normalized for direct use in network training by transforming them to the network's operating range, shaped to meet the requirements of the network input layer, and adapted to the nonlinearities of the neurons so that their outputs do not cross the saturation limits. The data is pre-processed in the ANN models by mapping data to a matrix row with minimum and maximum values from -1 to 1 for conducting proper analysis and improving the efficiency of the network training. Additionally, the time series data is prepared by shifting time by the minimum amount to fill input states and layer states for network open loop and closed loop feedback modes. This allows the original time series data to remain unchanged, easily customizing it for networks with different numbers of delays. Tapped delay lines are used to store previous values of the $x(t)$ and $y(t)$ sequences. Figure 12 shows a simple architecture of the NARX neural network.

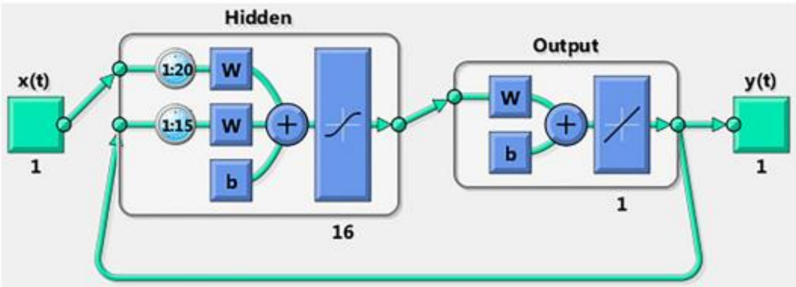


Figure 12: NARX neural network basic structure

Table 5: ANN algorithms adopted for the empirical studies

ANN ALGORITHMS	STUDIES
Convolutional Neural Network (CNN)	1
Multilayer Perceptron (MLP)	76
adaptive network-based fuzzy inference system (ANFIS)	5
Gated Recurrent Neural Network (GRNN)	5
Recurrent Neural Network (RNN)	3
Long short-term memory (LSTM)	2
Radial Basis Function (RBF)	9
Elman Neural Network (ENN)	1
Nonlinear Autoregressive Network with Exogenous Inputs (NARX)	1

3.3.9 SUMMARY OF ANN MODELS ADOPTED

In artificial neural network applications, the choice of the model adopted for a particular project affects the solution and performance accuracy in the long run. In this study, all models adopted go beyond a simple perceptron architecture hence employing some aspect of complexity through gates, deep layers, etc. to propagate the desired outputs. Through the analysis made, it was found that about 73.79% of the studies adopted a Multilayer perceptron (Feedforward) neural network for their solutions. Though problems related to time based functions usually adopt recurrent-based models, few studies adopted the RNN, LSTM, and GRNNs in their solutions though the models are affected by time of the day. The three therefore constitute about 9.71% of the entire pool of empirical studies.

3.4 INDEPENDENT VARIABLES

Selecting a "best subset" of input variables is a critical issue in forecasting. This is particularly important in data-driven techniques, such as artificial neural networks (ANNs) and fuzzy systems, as the performance of the final model is heavily dependent on the input variables used to develop the model. Selection of the best set of input variables is essential to being able to model the system under consideration reliably. When the available data set is high dimensional, it is necessary to select a subset of the potential input variables to reduce the number of free parameters in the model in order to obtain good generalization with finite data. The correct choice of model inputs is also important for improving computational efficiency. However, the topic of input selection is a difficult one (Fernando et al., 2005). This is especially true when the number of available input series is large, and exhaustive search through all combinations of variables is computationally infeasible. The inclusion of irrelevant variables not only does not help prediction but can reduce forecast accuracy through added noise or systematic bias (Utans et al., 1995). In this study, about 11 different input variables were explored for the modeling of the empirical studies. These were ambient temperature, fluid flow rate, solar radiation, wind speed, inlet fluid temperature, Raynold number, time of the day, storage temperature, tank volume, nano-fluid concentration, and relative humidity. From the study, it was found that the most used input variable for the modeling of solar thermal collector performance was solar radiation of the location while the Reynolds number and tank volume were rarely used. Table 5: shows the statistics of the use of the input variables in the studies.

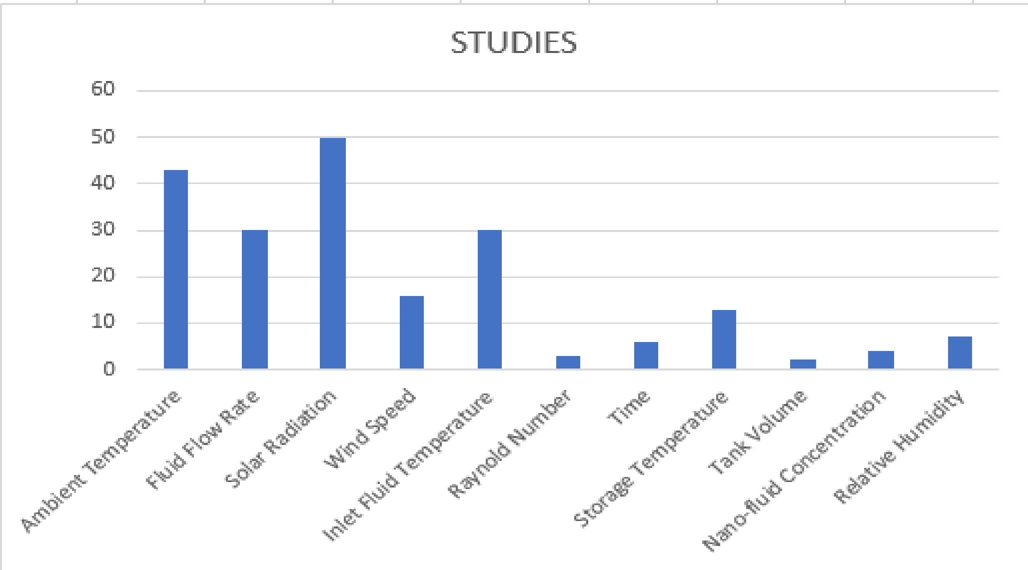


Figure 13: Summary of input variables used

3.5 DEPENDENT VARIABLES

Dependent variables are the output functions that are studied to model the performance of the solar thermal collector. Here, though some studies considered other variables, thermal efficiency and outlet temperature of the fluid were of greater importance to the authors of the works reviewed. About 41.86% and 25.58% of the studies focused on thermal efficiency and outlet temperature respectively. The rest are nusselt number, heat loss coefficient, heat collection rate, and other variables which were not treated as great importance in this study.

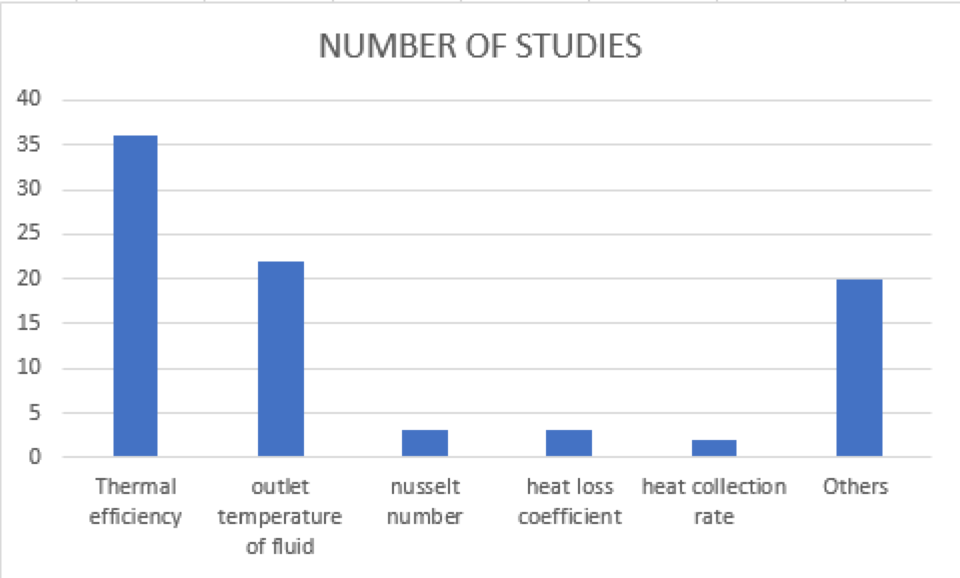


Figure 14: Summary of output variables considered

3.6 SOLUTION EVALUATION

The performance of neural structure is analyzed on the basis of minimum values of the following: Mean Absolute Error (MAE)(Sadeghi et al., 2020),

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{A,i} - Y_{P,i}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (14)$$

Sum of Square Error (SSE)(Caner et al., 2011),

$$SSE = \sum_{i=1}^{n}\left(Y_{A,i} - Y_{P,i}\right)^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (15)$$

Average Percentage of Error (APE)(Yedilkhan et al., 2019),

$$APE = \frac{1}{N}\sum\left(\frac{abc(A_i - P_i)}{A_i}\right) \times 100 \dots\dots\dots\dots\dots\dots\dots.. (16)$$

Coefficient of Variance (COV)(Ghritlahre & Prasad, 2018b),

$$COV = \frac{RMSE}{\frac{1}{n}\sum_{i=1}^{n} Y_{P,i}} \times 100 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (17)$$

Mean Squre Error (MSE)(Abidi et al., 2021),

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{A,i} - Y_{P,i}\right)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(18)$$

Mean Relative Error (MRE)%(Sadeghi et al., 2020) ,

$$MRE = \frac{1}{n}\sum_{i=1}^{n} 100 \times \left(\frac{\left|Y_{A,i} - Y_{P,i}\right|}{Y_{A,i}}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(19)$$

Margin of Deviation (MOD) (Abidi et al., 2021),

$$MOD = \frac{x_A - x_P}{x_A} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(20)$$

Mean Absolute Percent Error (MAPE)(Reyes-Téllez et al., 2020),

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{x_{A\,(i)} - x_{P(i)}}{x_{A(i)}}\right|}{n} \times 100(\%) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(21)$$

and Root Mean Square Error (RMSE)(Ajbar et al., 2021).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{A,i} - Y_{P,i}\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(22)$$

Furthermore, the optimal match of ANN expected data with real available data in terms of the following is used as a model output performance:

Coefficient of Determination (R^2)(Ajbar et al., 2021)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{A,i} - Y_{P,i}\right)^2}{\sum_{i=1}^{n} Y_{P,i}^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(23)$$

and Correlation Coefficient (R)(Dimri et al., 2019)

$$R = \frac{\sum_{i=1}^{n}\left(Y_{P,i} - \bar{Y}_P\right).\left(Y_{A,i} - \bar{Y}_A\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_{P,i} - \bar{Y}_P\right)^2.\left(Y_{A,i} - \bar{Y}_A\right)^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(24)$$

Correlation Coefficient (CC) (Yedilkhan et al., 2019),

$$CC = \frac{N\sum(A_i \times P_i) - \sum A_i \times P_i}{\sqrt{(N\sum A_i^2 - (N\sum A_i^2)(N\sum P_i^2 - (\sum P_i^2))}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(25)$$

Where Y_A , , and X_A are actual while, P_i and X_P are predicted values.

The value of R2, R, or CC determines the precision of ANN model forecast outcomes. The expected effects are said to be more accurate if the value of any is closer to unity. With the current review made, it was found that 12 evaluation metrics were adopted in the empirical studies. Though some articles justified their works using accuracy, they still relied on the underlying evaluation metrics that have been presented above. Figure 13 shows the statistics of how many studies adopted the individual metrics. Here, the most used metrics were MSE, $R^{2,}$ and RMSE while the rarely used metrics were MOD, CC, and APE.

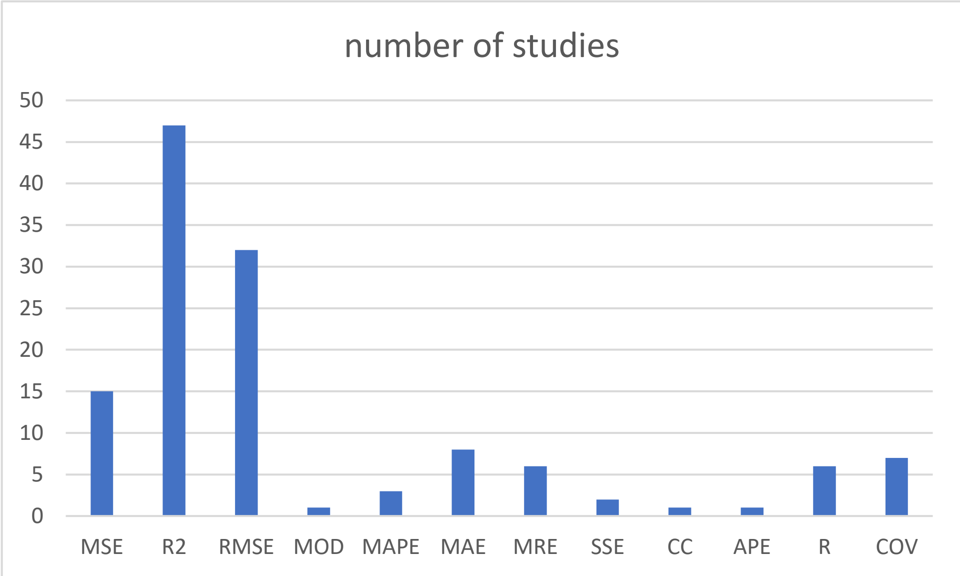


Figure 13: Statistics of the number of studies with adopted metrics

3.7 META-ANALYSIS

The last research question of the study was related to a statistical meta-analysis of the performance of ANN models. Ideally, this kind of investigation would have required the complete re-execution of the prediction models on a common dataset and using common evaluation metrics, so that they might have benchmarked. However, this is outside the scope of a Systematic Literature Review: rather, the goal is to synthesize the results reported in the primary studies, accepting the limitations that were observed during the analysis of the previous research questions. In this study, the impact of the ANN algorithm on the performance of output variable prediction was analyzed. A statistical meta-analysis aims at combining multiple studies in an effort to increase power over individual studies while improving the estimates of the effect sizes and resolving uncertainties when different studies disagree. Indeed, while individual studies are often too small for drawing reliable generalizable conclusions, their combination might provide less random error and narrower confidence intervals. Meta-analyses have also an important drawback: they cannot correct for the poor design and bias in the original studies. Nonetheless, the advantages are far more valuable than the few downsides if the analyses are carried out and interpreted carefully.

The first step in a meta-analysis is to compute, from each of the individual studies, the outcome of interest and summary statistics. meanwhile, not all the previous studies assessed the performance of the proposed models in the same way. To have a common basis and conduct a fair comparison, papers that evaluated the ANN models in terms of common evaluation metrics were carefully compared and analyzed: As shown in Table 6 from Appendix 1, about 20 studies used R^2 for evaluating their ANN algorithms. Here, the maximum value was 1.0 (Motahar & Bagheri-esfeh, 2020). Their study used irradiance, wind speed, ambient temperature, and relative humidity as input variables to predict the thermal output of solar water heaters using an MLP neural network. Here 120 data points were collected from Iran for the study. The minimum value on the other hand was 0.74430 (Diez et al., 2019). In this study, outlet temperature was predicted using solar radiation, ambient temperature, inlet temperature, and fluid flow rate as inputs to train an MLP neural network. The data points were taken from Spain with 59 samples. Within the entire study, on R^2, the mean value is found to be 0.97207.

Error level performance was evaluated using two main metrics: RMSE being and the extended form of MSE. The least error based on MSE was 0.00000194 (Bagheri et al., 2020). They collected 256 samples of data from Iran for the training of MLP with the following input variables: glass temperature, ambient temperature, insulation temperature, basin temperature, inlet water temperature, and radiation. The study therefore focused on the performance of solar desalination. The poorest value of MSE was attained to be 3.88 (Saravanakumar et al., 2013).

With the use of three predictors (ambient temperature, irradiance and mass flow rate), 21 samples of datapoints collected in India were used to train a MLP model for the prediction of outlet temperature of a Solar Air Heater (SAH). With reference to RMSE, the best performance yielded an error value of 0.0000059284 (Ghritlahre & Prasad, 2018). In the study, 96 data samples were taken from India to train a Gated Recurrent Neural Network (GRNN) for the prediction of thermal efficiency of a porous bed solar air heater. The input variables used are mass flow rate, wind speed, atmospheric temperature, inlet fluid temperature, fluid mean temperature and solar intensity. The poorest value being 5.5871 was attained by (W. Wang et al., 2017). Here, 700 data samples were taken from China to train Genetic Algorithm based back propagation Neural Network (GA – BP NN) to predict thermal efficiency of a parabolic trough solar collector. The following input variables were used: solar radiation intensity, wind speed of ambient, ambient temperature, flow rate, the inlet and the outlet temperatures of the cavity absorber. The rest of the evaluation used in few studies were of little concern in this study.

4. Discussion

This chapter highlights the significance of the findings attained in the previous chapter and how it correlated with existing literature. The problem statement coils around the need to enhance the performance of solar thermal collector, where experimental, analytical and computational techniques are implemented which require a lot of time to arrive at an accurate result. Theoretical based results, on the other hand, are suitable only for simplified models of the practical devices under many simplifying assumptions. Due to its simplicity, high speed and capability to solve complex and nonlinear relationship among the variables and extracted data, ANNs are therefore becoming the best choice of approach and many other thermal systems. Lack of comprehensive review on empirical studies conducted on this area therefore create a huge gap for further review. Holding unto the research questions posted for the research, a detail discussion is presented on the results achieved during the methodology applied for the study. The overall aim of conducting a systematic literature review with meta-analysis for the application of ANN on solar thermal collector performance created three specific niches for the results to be presented. The findings from the study are therefore highlighted and analyzed in this section of the report. The question posed, *"which solar thermal device and location of experimental data were used for the study?"* aimed at providing a theme of the data collection method. *"Which Artificial neural network models, independent variables, and dependent variables are widely employed in performance evaluation of solar thermal collectors?"* is an element of the second research question that emphasizes on the model choice for the ANN. The final research question emphasizes evaluation metrics stated as *"Which metrics are used to evaluate the performance of neural networks for performance modeling and evaluation of solar thermal collectors?"*

4.1 KEY FINDINGS

An extensive literature survey and meta-analysis performed in this paper were aimed at getting access to all academic materials that utilize neural networks as a framework for predicting and modeling solar thermal devices. The search criterion delivered a total of 86 published materials in the stipulated field of study which were used for conducting the study. Due to restrictions and other anomalies in search engines, this work does not guarantee an exhaustive search in the said field but is believed to cover a greater percentage of published works. Results from the study reveal that, the application of ANN on SWH where water is used as the heat exchanger dominates the pool of literature for the study. The simplicity of the design, construction, and analytical modeling of the device is therefore guaranteed to be cheap when using water as the heat-exchanging medium. With further study into the experimental location, the global participation area was found to be Asia. Since only two works (from North Africa)(Boukelia et al., 2017b) (Of, 2012) were conducted in Africa there is a huge gap in how African data influence the modeling criteria of ANN algorithms on solar thermal devices.

The application of MLP for the study of solar thermal devices dominates the entire pool of study with a contribution of 76 out of the 86 articles reviewed. Here, 77.63 % of articles used MLP as a solo model for their research while 22.37% of articles made comparative studies with other neural network models and optimization techniques such as genetic algorithms(W. Wang et al., 2017) and fuzzy logic (Shafieian et al., 2020). Huge attention is placed on the use of MLP for the performance study of the solar thermal collector. A research opportunity is found here; hence a study of other deep learning models in a comprehensive manner is highly needed. Within the predictor variables, model training was biased toward solar radiation, ambient temperature, and inlet fluid temperature. Though variables like fluid flow rate, wind speed, time of the day, storage temperature, Nano-fluid concentration, and relative temperature were also part of many trainings, Reynold number(Bhattacharyya et al., 2021) (Ghritlahre & Prasad, 2018c) (Maria et al., 2016) and tank volume (Sadeghi et al., 2020)(Sadeghi et al., 2021) were rarely involved. Future research can therefore treat these predictor biases as a research gap. Meanwhile, the highest R^2 obtained (W. Wang et al., 2017)(Mohanraj et al., 2009)(Xie et al., 2009)(Kulkarni et al., 2020) was 0.9999 which has a correlation with the location of the data source which is almost biased towards Asia. On the account of RMSE, the best was found (Ghritlahre & Prasad, 2018a) to be 0.0000059284.

5. Conclusion

This chapter will conclude the study by summarizing the key research findings in relation to the research aims and questions and discussing the value and contribution thereof. It will also review the limitations of the study and propose opportunities for future research. This study aimed to conduct a systematic literature review and meta-analysis on the application of deep learning in the performance modeling of solar thermal collectors. Using the PRISMA model for the study, the results indicate that the use of water and air as heat exchangers for the device is common as compared to Nano-fluids. Empirical studies on this field focus much on the Asian world like Iran and China. It was revealed by the research that 77.63 % of the articles used MLP as a solo model for their research while 22.37% of articles made comparative studies with other neural network models and optimization techniques such as genetic algorithms and fuzzy logic. Though, input variables like tank volume and Reynold number were not common in the studies as compared to irradiance and temperature components, future works call for their inclusion to find their significant impact on the study. Evaluation of the various deep learning models was based on common metrics like the coefficient of determinant, root mean square error, etc. It was found that, certain metrics like the Sum of Square Error, Average Percentage of Error, and Coefficient of Variance were rarely considered in the studies. The idea of combining all available metrics in one study for comparative purposes is therefore an issue of important discussion. Though the study reviewed about twenty years of empirical studies which might not be exhaustive, the upper quartile of the research period demonstrates an exponential growth in the field indicating research interest in the area. Future researches are therefore advice and directed to take the pain of coming out with a study that includes as many deep learning and other traditional machine algorithms to draw research conclusions.

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