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Article *in* Journal of Cleaner Production · April 2015

DOI: 10.1016/j.jclepro.2015.04.041

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Journal of Cleaner Production 104 (2015) 1–12

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Review

The artificial neural network for solar radiation prediction and designing solar systems: a systematic literature review

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ARTICLE INFO

Article history:
Received 18 December 2014
Received in revised form
8 April 2015
Accepted 13 April 2015
Available online 27 April 2015

Keywords:
Solar energy
Solar radiation prediction
Solar systems
Data mining
Artificial neural network

ABSTRACT

Solar energy generated by sunlight has a non-schedulable nature due to the stochastic environment of meteorological conditions. Hence, power system control and the energy business require the prediction of solar energy (radiation) from a few seconds up to one week in advance. To deal with prediction shortcomings, various solar radiation prediction methods have been used. Predictive data mining offers variety of methods for solar radiation predictions where artificial neural network is one of the reliable and accurate methods. A systematic review of literature was conducted and identified 24 papers that discuss artificial neural network for solar systems design and solar radiation prediction. The artificial neural network techniques were employed for designing solar systems and predicting solar radiations to assess current literature on the basis of prediction accuracy and inadequacies. Specific inclusion and exclusion criteria in two distinct rounds were applied to determine the most relevant studies for our research goal. Further, it is observed from the result of this study that artificial neural network gives good accuracy in terms of prediction error less than 20%. The accuracy of solar radiation prediction models is found to be dependent on input parameters and architecture type algorithms utilized. Therefore, artificial neural network as compared to other empirical models is capable to deal with many input meteorological parameters, which make it more accurate and reliable.

1. Introduction

Renewable energy resources have gained significant importance in the 21st century due to awareness of environmental pollution and depleting reservoirs of fossil fuels. The researchers are striving hard to make a pollution free environment by proposing carbon free technologies in different forms such as automobile, garments, home appliances and other energy consumption sectors (Köhler et al., 2013; Koroneos and Nanaki, 2012; Liu and Wang, 2013). Renewable energy is available through different natural resources such as solar, wind, geothermal, biomass and tidal etc. The research shows that people want to utilize renewable energy due to their concerns about environmental issues as well as limited available conventional energy resources (Yuan et al., 2015; Qazi et al., 2014). Solar energy is one of the most important clean, renewable energy resources, which comes directly from the sun in the form of radiations. The radiated energy is employed in two types of solar systems: (1) thermal and (2) electrical. Both forms of energy are used in variety of ways to make a clean environment. The solar collectors are designed to make decision analysis that is considered to have a wider potential for applications in the fields of renewable energy and sustainable design (Nixon et al., 2013; Fayaz et al., 2011). Solar radiation prediction is necessary on the broad level to build resourceful solar systems. For solar radiation prediction, many predictive data mining methods are successfully utilized, where, artificial neural networks (ANNs) are excessively used (Hepbasli and Alsuhaibani, 2011).

The global use of solar energy has grown significantly recently; the 100 GW milestone has already been surpassed in the first

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http://dx.doi.org/10.1016/j.jclepro.2015.04.041
0959-6526/

Nomenclature

Error calculation

BP	back propagation
MBE	mean bias error
MAPE	mean absolute percentage error
NRMSE	normalized root mean square error
R	correlation coefficient
R^2	absolute fraction of variance
RMSE	root mean square error
COV	coefficient of variation
GSR	global solar radiation

Input parameters

Lat	latitude
Lon	longitude
Alt	altitude
WS	wind speed
RF	rainfall
Mth	month
Avg	average
LW	long weave length
RH	relative humidity
AT	air temperature
TEMP	temperature
MOY	month of year/time
ATM	atmospheric pressure
DOM	day of month
SCG	scale conjugate gradient
RP	resilient propagation

quarter of year (2013), while solar power capacity was 40 GW in 2010 (Colak et al., 2013; IEA, 2013). Hence, solar energy produced on large scale and when it is grid connected, it needs to prediction of solar energy to balance the energy demand and supply. Hence, solar radiation prediction becomes vital for solar energy systems, which are designed to produce energy at large scales and/or are grid connected to balance the energy demand and supply. Modern studies deduced that many solar systems may function in an off/on manner in clear/cloudy time intervals. Therefore, it is indeed important to predict the solar radiations at different time intervals. This paper presents a brief review on data mining and detailed review on the artificial neural network as a tool for solar radiation prediction. The main contributions include the emphasis on the artificial neural network used in solar energy systems as well as for daily and monthly solar radiation prediction. The prediction error that is discussed in literature is measured through different metrics that is listed in above nomenclature list.

2. Research method

To advance our understanding in implementing solar radiation prediction models, the present study consisted of a systematic literature review with a specific focus on research related to prediction models and solar systems. A systematic review differs from a traditional general review as it adopts a replicable, scientific, and transparent process. The purpose of a systematic review of literature is three-fold (Brereton et al., 2007); (1) To present a fair evaluation of a research topic by means of a rigorous and systematic method; (2) To help in identifying any gaps in the current research in order to suggest further improvements; and (3) To summarize and provide background for new research activities. This leads to developing collective insights based on theoretical synthesis of existing studies. Previous researchers have argued that using such an approach to review literature can ensure that bias (i.e., systematic error) is limited; chance effects are reduced, and the legitimacy of data analysis is enhanced (Boehm and Thomas, 2013; Stechemesser and Guenther, 2012). The design of the systematic review reported in this paper started in November 2013. After several refinements and improvements, publication search was started in September 2014.

The Fig. 1 presents the research method that was adopted for systematic review.

2.1. Planning the review

This review is planned by proposing research questions relevant to the research objectives. The following steps present the data sources, search strategies, the publication selection and screening criteria.

2.1.1. Review objective and research questions

With the increased use of neural network methods in prediction, it has become important to study the role of neural network in solar radiation prediction. Therefore, the main goal of this work is to develop an understanding of solar radiation prediction using artificial neural network.

This study advocates the way how neural network techniques are more significant than other empirical methods to perform solar radiation prediction. Since research questions guide the design of the review process, specifying them is the most important part of any systematic review (Keele, 2007; Seuring and Müller, 2008; White and Schmidt, 2005). To fulfil these objectives, the research questions are formulated as follows:

RQ1: Which techniques of solar energy prediction are being addressed by researchers and how are the studies distributed across these techniques?

As current strategies and knowledge on solar energy radiation prediction and designing solar system is dispersed across many papers, the work will be used as a way to structure the analysis of the body of knowledge on a single work sheet on solar radiation prediction and designing solar systems. This will enable to determine which techniques get the most/least attractive results and can be most adventitious.

RQ2: How effective is the ANN modeling in the field?

The aim of this second research question is to assess the current maturity of predictive data mining method such as artificial neural network techniques. In this work, given the wide area of research on ANN techniques for solar radiation prediction and desiring solar system, many different areas can be envisaged to contribute better prediction. The current research will help researchers and solar power plant installers to define solar radiation data with greater precision in situations where meteorological stations are lacking.

2.1.2. Search strategy

After defining the research goals and questions, we started with the formulation of a formal search strategy to analyze all available empirical materials specific to the objective of this review. The plan involved defining the search space, which included electronic databases as shown in Table 1. This study performed two types of search to find publications relevant to the scope of the review. The first type was an automatic search performed on the following publishers' databases: ACM (portal.acm.org), IEEE (ieeexplore.ieee.org), ScienceDirect, Springer (springerlink.com), Wiley and ISI web

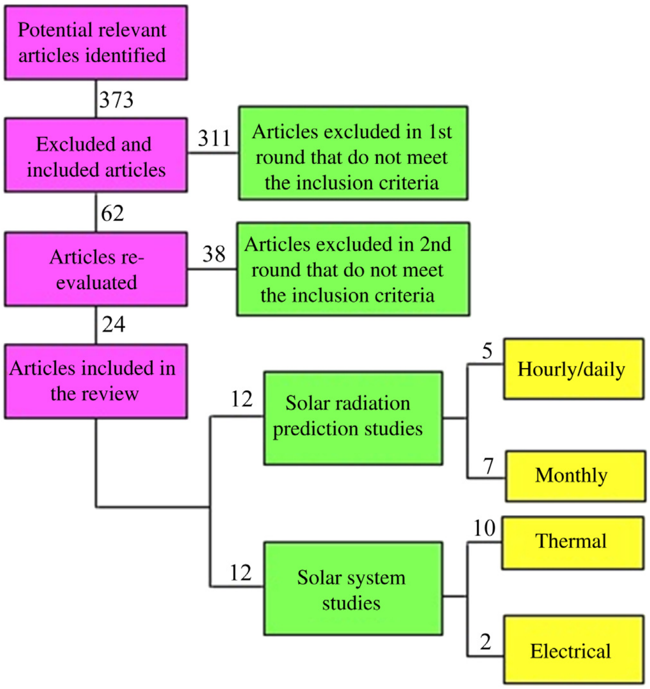

Fig. 1. Systematic review flow diagram.

Table 1
Search sources.

Electronic databases	ACM Digital library IEEE Xplorer SpringerLink ISI web of knowledge ScienceDirect Wiley
Searched items	Journal, workshop and conference papers
Search applied on	Full text to find papers within the scope and not omit any paper that did not include our search keywords in the title or abstract.
Language	English
Publication period	From January 2006–2013

of knowledge. The second type was a manual search on the following workshops, conference, and journals: ASME 2011 5th International Conference on Energy Sustainability & 9th Fuel Cell Science, Engineering and Technology Conference, First International Workshop on Knowledge Discovery and Data Mining, IEEE, 2008 and Journal of Renewable Energy. The manual search was made based on the authors' collective observations during the pilot searches. This supplementary strategy aimed to add any potential works that might have been left out.

2.1.3. Search criteria

The search criterion used for this review is defined as follows. The first step begins by setting certain practical screening criteria to ensure that only quality publications are included in the review. During the first search, therefore, conference articles, working papers, commentaries, and book review articles were excluded, aiming instead for a focus on journal publications (Seuring and Müller, 2008). This delimitation also secured the focus on quality publications related to solar radiation prediction and related concepts. No other quality criteria were used (e.g., journal rankings) for filtering; indeed. The search also excluded articles that were not peer-reviewed or not written in English. The search string is developed by specifying the main terms of the phenomena under study. A number of pilot searches were performed to refine the keywords in the search string using trial and error. The terms whose inclusion did not yield additional papers in the automatic searches are removed. After several iterations, following search string is settled depicted in Table 2.

2.1.4. Inclusion and exclusion criteria

After string search, several strings in ISI WoS and scanned the results to check their quality, and the inclusions of well-known relevant literature are filtered. The purpose of the present study is to focus on artificial neural network models for solar radiation prediction and solar systems design; only articles that discussed monthly or hourly prediction models were included. More specifically, the inclusion criteria for articles selected for full analysis were as follows:

(a) Inclusion criteria:

1. Monthly solar radiation prediction models. Studies that discussed solar radiation prediction on the monthly basis with implementation of artificial neural network techniques were retained.
2. Hourly solar radiation prediction models. Studies that discussed solar radiation prediction on the hourly basis with implementation of artificial neural network techniques were retained.
3. Solar systems; Studies that explicitly used artificial neural network techniques to design solar systems, such as solar water heating systems, solar refrigeration systems, PV panels, etc. were retained.

(b) Exclusion criteria:

1. Studies that do not focus explicitly on artificial neural network methods for solar radiation prediction, but only refer to artificial neural network as a side work.
2. Studies that do not discuss artificial neural network techniques for solar system design.
3. Studies that do not meet inclusion criteria.

Based on the criteria assessment, each article was either included or excluded. In cases where researchers' views on the abstract screening differed, researchers scanned the entire article for relevance. This time-consuming process resulted in including 24 articles out of 62 that were included after the inclusion criteria.

Table 2
Keywords operationalized for search.

Search clouds		Exemplary search string
Data mining	Solar radiation prediction	
Data mining, artificial neural networks, prediction models	Solar radiation prediction, solar systems, yearly solar radiation prediction, monthly solar radiation prediction, daily solar radiation prediction	Solar radiation prediction and data mining, solar radiation prediction or data mining, yearly solar radiation prediction, monthly solar radiation prediction, daily solar radiation prediction, solar systems and data mining techniques, solar systems and artificial neural networks, solar radiation prediction and neural networks

2.2. Conducting the review

This section presents the findings of search and extraction of information from relevant sources and databases.

2.2.1. Study search and selection

By following the search strategy (previously explained in Section 2.1.2), the selected electronic databases were searched and the studies retrieved. In depth analysis of the studies' titles and abstracts was made by one of the researchers (Round 1) by applying the inclusion criteria.

As a result of this first round of classification, we ended up with 62 candidate studies.

Then, in Round 2, the pre-selected studies were assessed by a second (one of the co-authors) and a third (independent and experienced) researcher in order to apply the exclusion criteria. To review the agreements and disagreements raised by the researchers in their assessments, we conducted a face-to-face consensus meeting. For the papers where consensus was not reached, the three researchers read the entire paper and then excluded the studies based on the defined exclusion criteria. Therefore, final selection consists of 24 studies (see in Table 3). The original search retrieved 373 studies as shown in Table 3. Thus, this systematic literature review is based on 24 articles with a specific focus on solar system and solar radiation prediction implemented with ANN models.

2.2.2. Data extraction and analysis

The data extraction process is defined to identify relevant information from the 24 included primary studies that are related to the research questions. The data extraction process includes the following: First, we set up a form to record ideas, concepts, contributions, and findings of each of the 24 studies. Using this form ensures subsequent higher-order interpretation. The following data were extracted from each publication: (i) review date; (ii) title; (iii) authors; (iv) reference; (v) database; (vi) relevance to the theme, i.e. solar radiation prediction, solar systems, ANN models, methods, techniques; (vii) future work; (viii) country/location of the analysis; (ix) year of publication.

Once the extraction was completed, we used content analysis of each study. For the analysis of these articles, an expert knowledge was used for publication selection. The study included the relevant publications of which the authors were aware either on their own or because of having been informed by a colleague, but that had not been identified through the automated and manual searches. These were mainly studies that were accepted for publication but not yet available from the publishers when the automatic search was performed. In either case, publications added through expert knowledge were subject to passing the same inclusion criteria applied to automatic and manual searches. We also computed the Kappa coefficient of agreement, which corrects for chance agreement. The value of the Kappa coefficient was calculated to 0.62, which indicates good agreement (Landis and Koch, 1977). All the disagreements were resolved through a discussion. The systematic literature review process places strong emphasis on the importance of ensuring a high level of validity and reliability. We also computed the Kappa coefficient of agreement, which corrects for chance agreement. The value of the Kappa coefficient was calculated to 0.62, which indicates good agreement (Landis and Koch, 1977). All the disagreements were resolved through a discussion. The literature review process and analysis protocol was discussed with researchers both within and outside the field. This approach enabled us to increase the validity of the literature review by decreasing the risk of the file drawer effect, a bias among unpublished studies that may distort systematic reviews. Also the researchers carefully explained each of the steps followed during the systematic literature review to increase future replication and ensure accuracy.

Table 3
Search results and filtered publications according to search term.

Database	Retrieved	Round 1		Round 2	
		Included	Excluded	Included	Excluded
ACM Digital Library	110	10	100	3	7
IEEE Xplore	75	14	61	4	10
SpringerLink	34	7	27	3	4
ScienceDirect	80	10	70	8	2
Wiley	20	7	13	4	3
ISI web of knowledge	54	14	40	2	12
Total	373	62	311	24	38

3. Findings of review

In this section and the next, results from the systematic literature review are reported. In particular, the results of the review are gathered in the light of data mining, predictive data mining techniques (ANNs), ANN for solar systems and ANN for solar radiation prediction. It should be highlighted that one of the key concepts that guide this research is that of solar radiation predication and solar systems. This is successfully growing by the use of predictive data mining techniques. In this context, the artificial neural network is competently performing. The details of important concepts are described in the following sections and sub sections.

3.1. Data mining

Data mining is the process of discovering hidden patterns and analyzing data from diverse aspects and summarizing it into practical knowledge. This can be used to enhance revenue, decrease cost, or at times both. Data mining usage in prediction and manufacturing started in the 1990s (Suehrcke and McCormick, 1992). The predictive analysis consists of different steps. The steps applied in knowledge discovery databases are illustrated in Fig. 2 adopted by Luo (2008). The process has three phases:

- Initial exploration
- Model building/validation
- Deployment (i.e., applying the model to new data in order to generate predictions).

3.1.1. Initial exploration

The preliminary investigation covers data preprocessing, which may involve (1) cleaning the data, (2) data transformation, and (3) data reduction. The data matrix employs data preprocessing techniques to increase the data input quality. Data preprocessing is significant to any data mining approach, due to its prevailing effect on the efficiency and accuracy of data mining algorithms (Sadoyan et al., 2006).

3.1.2. Model building and validation

Model building and validation include selecting the finest model among others according to predictive performance. Although model selection appears to be a simple task, it often involves a very detailed procedure. The available models are based on “competitive evaluation of models,” which is essentially predicting the best model by comparing various models with the same data set. All steps involved in the knowledge discovery process are essential, and model selection is indeed crucial (Khoshnevisan et al., 2014).

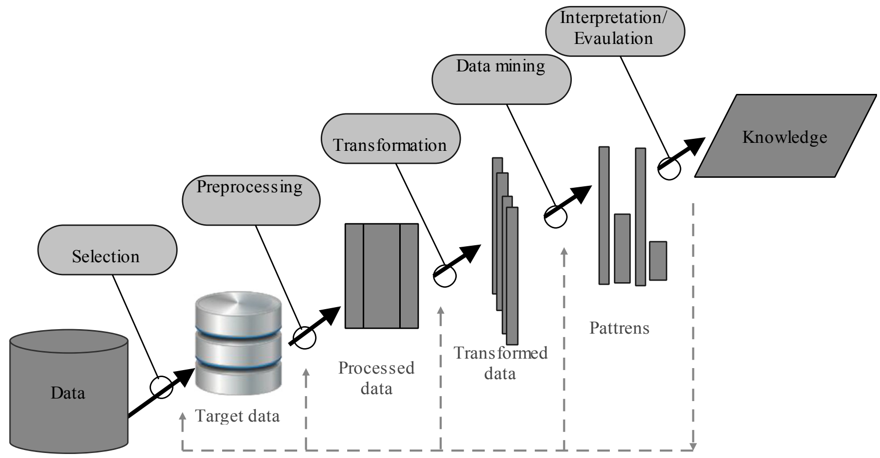

Fig. 2. Data mining phases for predictive analysis.

3.1.3. Deployment

Deployment is the final stage, and involves applying the selected model to new data and presenting the results. The applied model generates forecasts for the expected outcome as a result of the data mining approach (Rupnik and Jaklič, 2009). This phase is accountable for the deployment of data mining in operational business processes. Precisely at this final stage, the best performing model among others is deployed to make predictions, which can then be used to make business decisions.

3.2. Predictive data mining techniques and artificial neural network

The ultimate goal of data mining is prediction and predictive data mining is the most common type of data mining. These predictive techniques include: Bagging (Voting, Averaging), Boosting, Stacking (Stacked Generalizations) and Meta learning (Cambria et al., 2015b). Bagging (stands for Bootstrap Aggregation) is the way to decrease the variance of prediction by generating additional data for training from original data set using combinations with repetitions. It is to produce multisets of the same cardinality/size as original data. Boosting is an approach to calculate the output using several different models and then average the result using a weighted average approach. By combining the advantages of these approaches by varying weighting formula one can come up with a good predictive force for a wider range of input data, using different narrowly tuned models. Stacking is a similar to boosting, however, it doesn't work for just an empirical formula for weight function, rather a meta-level is introduced and use of another model/approach is required. It is to determine what models perform well and what badly given these input data. The concept of meta-learning is to combine the predictions from multiple models. It is particularly useful when the types of models included in the project are very different. In this context, this procedure is also referred to as Stacking (Stacked Generalization).

The artificial neural network (ANN) is one of the most common methods in predictive data mining. As it is capable of performing predictive data analysis, it has evolved as advanced data mining tools in cases where other techniques may not produce acceptable predictive results (Behrang et al., 2010; Journée and Bertrand, 2010; Martí and Gasque, 2011). ANN has successfully been employed for the solar radiation prediction and solar systems design that is essential for clean environment. Recently ANN is also used for predicting the environmental impacts by assessing the green house crops (Khoshnevisan et al., 2014, 2013). ANNs utilize neurons and simple processing units, combine data, and store relationships between independent and dependent variables. It consists of several interconnected layers of neurons.

There are two kinds of ANN: (1) Single layer and (2) multi-layer Preceptor (MLP). The latter is widely used in NN models, and it consists of three interconnected parts. The input layer is under the first part, and the output layer is presented by the last part, while in the middle, there is one or more layers called hidden layers. Inside each layer there are several neurons (nodes). Every node in a layer is connected to the nodes in the adjacent layer with deferent weight. These weights have no meaning initially, but after training they will contain meaningful information. Signals follow this way through these layers by first passing through the input layer. Subsequently, they pass through a hidden layer then through the output layer. In this process, each neuron receives signals from an adjacent layer in the previous layer (X_{ij}). However, the signal comes with its weight (W_{ij}), summed up with the bias (b_j) contribution. This can be expressed mathematically as:

$$\text{net}_j = \sum_{i=1}^{n} (X_i V_{ij} + b_j) \tag{1}$$

The output of neurons is then calculated by applying an activation function given by Table 4 on the total input computed by Equation (1). In the first iteration if the computed output does not match the unknown target values, it means that NN encounters an error, at which time a portion of this error will be feedback through the network to adjust the weight and bias of each neuron again. For the next iteration, the error will be less than before. Errors during the learning process are computed with Equations (2)–(4) (Sözen et al., 2004). This procedure is continuously repeated for each set of input until there is no quantifiable error or the limit where errors will be smaller than a specified value.

$$R^2 = 1 - \left(\frac{\sum_j |t_j - o_j|^2}{\sum_j |o_j|^2} \right) \tag{2}$$

$$\text{RMS} = \left(\frac{1}{p} \sum_j |t_j - o_j|^2 \right)^{\frac{1}{2}} \tag{3}$$

$$\text{MAPE} = \left(\frac{o - t}{o} \times 100 \right) \tag{4}$$

Table 4
Activation function.

Function	Definition	Range
Identity/Linear	X	$-\infty < x < \infty$
Logistic (Logsig)	$\frac{1}{1-e^{-x}}$	$0 \leq x \leq +1$
Hyperbolic (Tansig)	$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	$-1 \leq x \leq +1$
Exponential	e^{-X}	$0 \leq x < +\infty$

where p is the pattern, o is the output value and t represents the target value.

ANN uses several models such as feed-forward and feedback propagation for prediction. Information moves in single direction for the feed-forward network, so there are no cycles or loops in this network (Auer et al., 2008). Supervised learning is employed in propagation; it requires a data set of the desired output for many inputs, composing the training set. Fig. 3 presents a standard pipeline for solar radiation prediction through ANN. It is deduced from Fig. 3 that the data is taken as an input parameter and stored in database. After then, some data is used for training and some part is used for testing. The feedforward and feed backward are the two types of ANN models that are used to further process the data. Once the models are developed the error calculation is carried out for the purpose of accuracy. At the final stage, the selection of successful model for prediction is established.

The artificial neural network is trained with different geographical inputs, inputs that may use various terminologies as listed in Table 1. Neural Networks are analytic techniques modeled in three main stages: (1) similar to (hypothesized) learning processes in the cognitive system, (2) neurological brain functions, and (3) capable of predicting new observations (on specific variables) from other observations (on the same or other variables) after executing a learning process from present data.

In literature, there are several different empirical models available for solar radiation prediction. Each of these models has uncertainty in terms of solar radiation prediction. For example, the most popular empirical model is Angstrom model (Cambria et al., 2015a). This empirical model predicts the solar radiation based on give bright sunshine hours and extraterrestrial solar radiation. Hence, it cannot be used to extend solar radiation prediction at every location. Some parameters could have impact on accurate solar radiation prediction such as the terrain, humid, weather temperature and wind speed etc. (as example). To cope with these challenges of input parameters, artificial intelligence techniques such as artificial neural networks (ANN) are successfully applied. In the present work, we will review the studies that use ANN models for solar radiation prediction and solar system design. ANN is widely used with coming time in different application for the purpose of prediction. The depicted graph in Fig. 4 shows the growth rate of ANN since 2001–2013. The graph is based upon random search of articles that have implemented ANN during the period of 2001–2013.

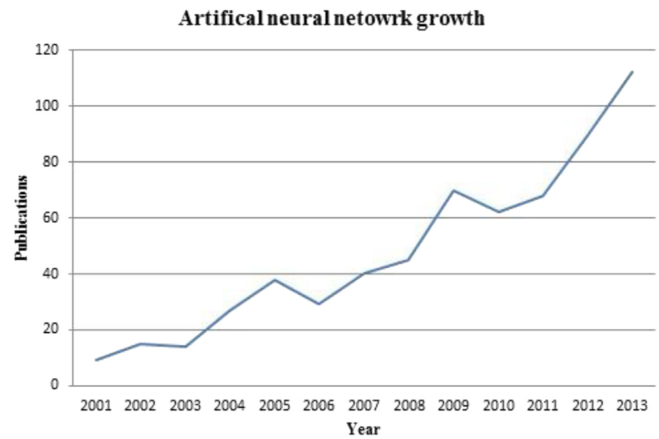

Fig. 4. Distribution of publications for solar radiation prediction through artificial neural networks from 2001 to 2013.

In this review, neural network-based (ANNs') systems generally developed in the last 10 years from 2005 to 2014 have been discussed.

3.3. ANN for solar energy systems

Solar energy prediction is quite challenging due to its variability and irregularity. Therefore, it is essential to predict solar radiation/power produced by sun rays for different time intervals. There are mainly two sorts of solar energy systems employed, namely thermal and electrical. Thermal solar systems are often applied for space heating, space cooling, heat generation processes and water heating (Khoshnevisan et al., 2013). Solar power is converted into electricity in two ways: (1) directly through photovoltaic (PV) cells, and (2) indirectly by concentrated solar power (CSP). Owing to the inconsistent nature of solar energy incidence, solar system performance is not stable. Therefore, solar system prediction has become necessary for electrical and thermal loads. There are numerous prediction methods, but more recently artificial neural networks (ANNs) have received extensive attention. ANN modeling helps with water heating using solar energy. The system has proved 40% efficiency by using solar radiation according to experiment. Additionally, 18 kW maximum power was supplied to the system at noon and 6 kW minimum in the afternoon (Cetiner et al., 2005).

The work proposed by Karatepe et al. (2006) describes PV module modeling using ANNs. The trained network was compared with other empirical models using multiple parameter combinations. The obtained comparison results for the proposed models were satisfactory and can be used for any type of PV module and power electronics studies where online application is applicable. To enhance solar cell performance, data mining supported by

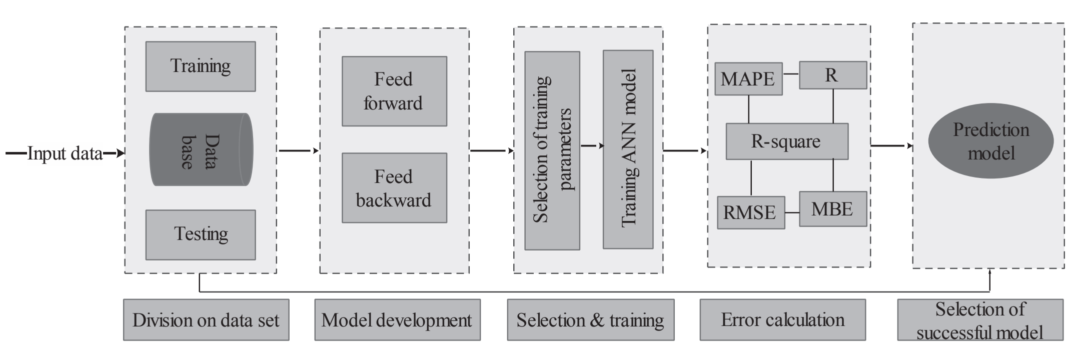

Fig. 3. The standard ANN solar radiation prediction pipeline.

theoretical calculations was used by Kusama et al. (2007). The results indicate a novel direction for developing an improved electrolytic solution by using base additives for dye-sensitized. Kalogirou et al. (2008) designed a fault diagnostic system (FDS) using ANN for a solar water heater (SWH) that consists of a prediction module, a residual calculator and the diagnosis module. The system can predict collector faults and faults in pipe insulation. The various input values for system faults are used to validate the system. A study of Mohanraj et al. (2009) predicted the DXSAHAP parameter of system performance based on ambient parameters by successfully training an ANN network. Results demonstrate that the performance prediction of a DXSAHP using ANN is valid. With few experiments, this novel approach assists researchers to predict the performance of a DXSAHP at different intensities.

The authors (Souliotis et al., 2009) presented a work on forecasting the performance of an Integrated Collector Storage (ICS) prototype, where a suitable artificial neural network (ANN) and TRNSYS are collectively utilized. According to experimental results, the proposed method is efficient for such predictions. The presented method can be applied to model systems that are either difficult to model analytically or whose model is not available. The proposed Artificial Neural Networks (ANNs) to model a solar-assisted air-conditioning system fitted based on an absorption chiller and provided only with solar collectors (Rosiek and Batlles, 2010). With the ANN model, the results are accurate and satisfactory, with calculated Root Mean Square Error (RMSE) of less than 1.9%. In this paper, the authors developed a reliability-tested, novel neural network-based monitoring and fault detection method using a solar hot water system. As seen in the results, real-life operating conditions are similar to simulation-based training with easy and correct fault detection in the field. With the proposed method it may possible to improve the reliability of SHW systems (He et al., 2012).

The study conducted by He et al. (2011) designed and tested a real-time solar hot water (SHW) fault detection system. The presented work used a hierarchical Adaptive Resonance Theory (ART)-based neural network fault detection module and the fault detection system included a data acquisition module. The simulation and experimental results signify that the trained fault detection system is capable of detecting expected faults including pump faults, impeller degradation, thermo-siphon and potentially unexpected errors. The solar coefficient of performance (COP) of an ice-producing solar periodic refrigeration system is predicted by Laidi and Hanini (2013), which works with an activated carbon (AC)/methanol pair proposed by the ANN model. The prediction with ANN achieved a very small error and the proposed interface can be used effortlessly. In order to develop an optimizing control strategy, research work presented by Porrazzo et al. (2013) applied a solar powered membrane distillation system. A neural network (NN) model of the system was trained and tested with purposely collected experimental data. Subsequently, the NN model was applied to process performance analysis under several operating conditions. With the proposed control system, the experimental tests increased distillate production.

In another research study, the artificial neural networks (ANNs) is used to predict the performance of large solar systems (Kalogirou et al., 2014). In this study, the ANN method helped to predict the expected daily energy output for typical operating conditions, as well as the temperature level the storage tank could reach by the end of the daily operation cycle. The results obtained from the method were also compared to the input-output model predictions with good accuracy whereas multiple linear regression could not give as accurate results. It can be concluded that the ANN effectively predicts the daily energy performance of the system; the statistical correlation factor R^2 value obtained for the training and validation data was 0.9273 and 0.9327. The proposed approach can be utilized to compare design performance predictions with actual system performance, as well as for the early detection of potential malfunctions. Fig. 5 shows the different kind solar systems based on ANN that are discussed in this study.

3.4. ANN for solar radiation prediction

In present times, the increasing number of solar systems has boosted the importance of solar radiation prediction. Many solar radiation prediction models are being developed for hourly and monthly basis readings. Hereby, monthly and hourly solar radiation prediction estimated by ANN and other comparative models is discussed. The comparison of ANN and other empirical models are based upon prediction error that indicates its accuracy level. The accuracy of solar radiation prediction is based upon the common statistical error measures such as MAPE, MPE, RMSE, R and R^2. The mostly commonly used measure is MAPE; it is the Mean Absolute Percentage Error (MAPE) which represents the difference between the predicted and real values. A value of more than 50% for MAPE indicates an inaccurate prediction. However, if the MAPE value is between 50% and 20%, a reasonable prediction has been obtained. If MAPE is between 20% and 10%, it means that a good prediction has been achieved, while the best prediction is only achieved when MAPE is less than 10% (Khoshnevisan et al., 2013). The values obtained from these accuracy formulas are noted for monthly/daily, hourly solar radiation prediction and depicted in Tables 5–7.

3.4.1. Monthly solar prediction

The climatic conditions of a location make solar radiation essential to the prediction and design of a solar energy system. Monthly average solar radiation is adopted as data source for solar radiation prediction, as daily solar radiation series is non-stable due to the fast weather changing. Monthly solar radiation prediction is carried out by different researchers by using ANN.

A feed-forward-back-propagation neutral network with a single hidden layer was employed by Jiang (2008). Solar radiation data from eight cities was used to train the neutral networks while data from Zhengzhou was used to test the predicted values. The coefficient of determination, R^2, was 0.90, signifying enhanced prediction accuracy. In this study, the ANN model is also compared with Zhou's empirical models (Ozgoren et al., 2012), after which the performance is compared with mean percentage error (MPE), mean bias error (MBE) and roots mean square error (RMSE). According to the result comparison, the ANN model provides the best results among the three solar prediction models.

An ANN model developed by Alam et al. (2009) aim to estimate monthly solar radiation in India at ten stations for different climatic conditions. Data for one year was utilized to train and test the neutral network. The inputs of different combinations were provided to train the feed-forward-back-propagation. The coefficients of determination (R^2) for all stations were higher than 0.85, indicating a strong correlation between diffused solar radiation and selected input parameters. The summer and winter results coincide with a 1:1 ratio, but the rainy season results lies on both sides of the standard 1:1 line. This deviation in obtained results shows that the maximum error rate in ANN computation occurs in the rainy months. In addition, the proposed model was compared with other empirical models, and ANN proved better prediction ability.

The authors (Şenkal and Kuleli, 2009) proposed artificial neural networks (ANNs) for the estimation of solar radiation in Turkey. The proposed model used resilient propagation (RP), scale conjugate gradient (SCG) learning algorithms and a logistic sigmoid transfer

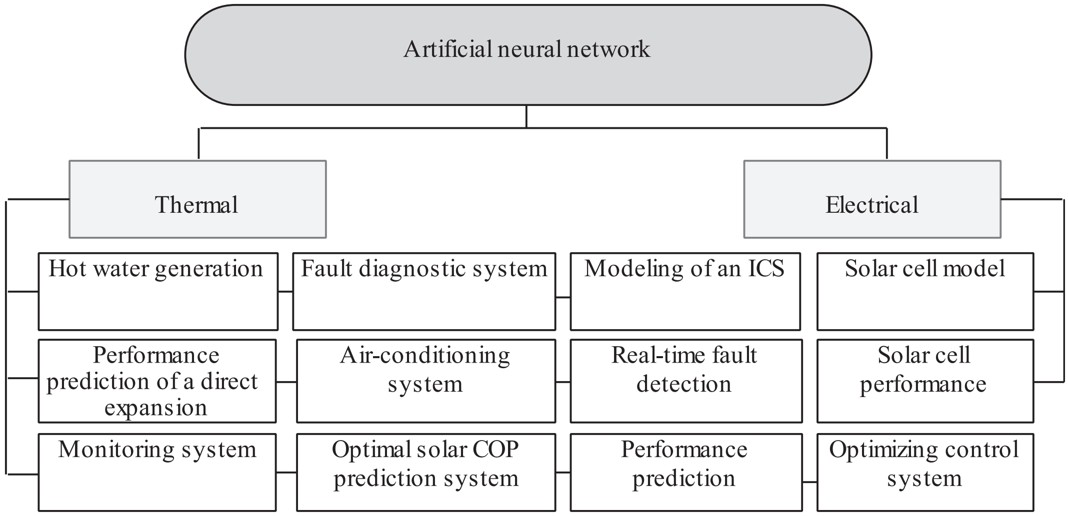

Fig. 5. Artificial neural network based solar systems.

function with neural network. The neutral networks were trained by meteorological data for August 1997 up to December 1997 for 12 different cities in Turkey. Nine cities were used for training and three cities for testing. The obtained correlation results for 12 cities indicate relatively good agreement between the observed ANN values and the predicted satellite values.

The monthly global solar radiation was predicted by Jiang (2009) for 8 typical cities in China. The feed-forward back-propagation algorithm with input parameters (latitude, longitude, altitude, sunshine percentage) was applied in the analysis. The proposed ANN model and the other seven empirical regression models were compared with each other. The comparison was carried out on measured data on the basis of mean percentage error (MPE), mean bias error (MBE) and root mean square error (RMSE). The comparison results indicate that the proposed ANN model has the minimum prediction errors for Shenyang, Chengdu and Zhengzhou, while ANN does not provide more accurate rankings of Kashi and Geermu. The other empirical models have a low error (MP −3.75% for Kashi and MPE 5.43% for Geermu). The results confirm the capability of the ANN model to

Table 5
Performance of methodologies applied for monthly solar radiation prediction.

Ref.	Location	Input parameters	No. of stations	ANN type	No. of neurons	Prediction error	Data recording intervals
Jiang (2008)	China	Solar radiation, sunshine hours, Temp, rainfall, ATM, humidity	9	Feed-forward back propagation	7	MPE (%) 1.55 MBE (MJ/m^2) −0.040 RMSE (MJ/m^2) 0.746	Jan 1995–Dec 2004
Alam et al. (2009)	India	Lat, Lon, Alt, time, MOY, AT, RH, RF, WS, LW.	10	Multilayer feedforward	13	RMSE (%) 8.8 (h) RMSE (mth) 4.5	Jan 2009 –Dec 2009
Şenkal and Kuleli (2009)	Turkey	Lat, Lon, Alt, Mth, mean diffuse radiation, mean beam radiation	12	RP, SCG Learning algorithms &logistic sigmoid transfer function	6	RMSE (%) 0.08	Aug 1997–Dec 1997
Jiang (2009)	China	Lon, Lat, Alt, Sunshine percentage	8	Feed-forward back-propagation	7	R^2 0.95 MPE (%) −4.96 MBE (MJ/m^2) −0.78 RMSE (MJ/m^2) 0.86	1995–2004
Koca et al. (2011)	Turkey	Lat, lon, alt, month, average cloudiness sunshine duration average wind velocity average humidity average TEMP	9	Back propagation	8	RMSE (%) 3.58 R^2 0.9906	Jan 2006–Dec 2006
Qin et al. (2011)	Japan	Lat, lon, alt	12	Multi-layer feed-forward	22	R (%) 0.89 RMSE (%) 0.86	Jan 2001–Dec 2007
Ozgoren et al. (2012)	Turkey	Lat, lon, alt, Mth, mean land surface temperature	27	Feed-forward back-propagation	20	MAPE (%) 5.34 R 0.9936	Jan 2000–Dec 2006

Table 6
Performance of methodologies applied for hourly solar radiation prediction.

Ref.	Location	Input parameters	No. of stations	ANN type	No. of neurons	Prediction error	Data recording intervals
Mellit and Pavan (2010)	Italy	Daily solar irradiance, mean daily air TEMP, DOM	41	Feedforward	17	RMSE (%) 13.14 MBE (%) 19.00 R (%) 98.95	July 1st 2008–May 23rd 2009 Nov 23rd 2009–Jan 24th 2010
Hasni et al. (2012)	Algeria	Mth, Day, Hour, TEMP, RH	1	Back propagation	3	RMSE 0.1720 MAE 2.9971 R^2 0.9999	02 Feb–31 May 2011
Notton et al. (2012)	Ajaccio	Hour, declination, zenith angle, horizontal global solar irradiation, extra-terrestrial horizontal solar irradiation	1	Feedforward back-propagation	40	RMSE (%) 6 RMAE (%) 3.5	Jan 2006–Dec 2010
Benmouiza and Cheknane (2013)	Algeria	Global horizontal solar radiation time series	1	Feedforward	13	RMSE (Wh/m^2) 64.34 NRMSE 0.2003	1st Nov 1996–31st Dec 1996
Chen et al. (2013)	Singapore	TEMP Solar radiation Sky condition	1	Feed-forward Neural Network with fuzzy logic	–	MAPE (%) 6.03	–

predict solar radiation values accurately. Additionally, the coefficient of determination (R^2) value obtained for the data set is 0.95, which shows good agreement between measured and predicted time series.

ANN was employed by Koca et al. (2011) as well, to identify the solar radiation parameters for seven different stations in the Mediterranean region of Anatolia. Prediction was based on data from 2005, 2007 and 2008, while data from 2006 was used for testing. The outcome indicates that the ANN-based model was highly accurate for solar radiation prediction in the chosen region as seen from prediction error values depicted in Table 5.

In this study, the ANN model seems promising for evaluating the solar resource potential in places where there are no monitoring stations in Mediterranean region of the Turkey. The study shows that ANN model seems promising and can be used to predict solar radiation for any region if provided with comprehensive values. The error values for ANN are measured on R^2, RMSE, and COV. The R^2 values were affected by the number of input parameters. The results indicated that the best prediction was for the city of Antakya, and little differences (or deviations) were found for Burdur. However, the best value was obtained to be 3.58% for Isparta.

The authors (Qin et al., 2011) proposed a mathematical relationship between measured monthly GSR and several high level remote sensing products based on ANN. The ANN comprised monthly averaged land surface temperature (LST), Moderate Resolution Imaging Spectra radiometer (MODIS), month, MODIS enhanced vegetation index, the number of days prior to land surface temperature (LST) retrieval performance, and Tropical Rainfall Measuring Mission satellite (TRMM) monthly precipitation. The proposed model was compared with other empirical models on metrics of correlation coefficient (R), root mean squared error (RMSE) and relative root mean square error (RRMSE). It is concluded from the results that none of the transfer functions affect ANN configuration behavior. However, increasing the number of neurons by more than ten in the hidden layer hardly improves the training output. The trained ANN is used to regain a GSR estimate at these four stations, which proves the ANN method outperforms the Japan aerospace exploration agency (JAXA) retrieval method at these sites; moreover, Yang's/or Young's method also performs well. The yang's method may retrieve GSR with high accuracy, but does not estimate GSR on regional scales. Therefore, the proposed ANN is used to retrieve GSR at regional stations for improved accuracy. Robust results from using ANN were achieved by using 12 neurons in the hidden layer and a hyperbolic tangent sigmoid function.

An ANN model based on multi nonlinear regression was developed by Ozgoren et al. (2012) to estimate monthly mean global solar radiation at any place in Turkey. The feed-forward back-propagation was used with geographical input parameters (attitude, longitude, altitude, month and mean land surface temperature) in different combinations. The proposed ANN model was compared with the MNLR regression model to obtain comparative results. The derived results are based on the MAPE and correlation coefficient (R) for the comparison between observed and estimated global solar radiation. For the testing data set, the maximum MAPE was found to be 7.05% for the Sakarya meteorological station, while the best reading obtained was 3.83% for the Kayseri meteorological station. Furthermore, for a meteorological place, the maximum correlation coefficient between the predicted and actual values noted was 0.9978. On the other hand, for the Sakarya meteorological station, the minimum correlation coefficient noted was 0.9911. Evidently, the MNLR model values are higher than the MAPE values of the ANN; therefore, ANN is considered to perform best compared with other MNLR models. The aforementioned techniques are summarized in Table 5.

3.4.2. *Hourly solar radiation prediction*

In some application we need to predict solar radiations on hourly basis. Some of which are carried on hourly solar radiation prediction are discussed here. An ANN-based 24 h forecasting of solar irradiance was developed by Mellit and Pavan (2010) from Trieste, Italy. The multilayer perception (MLP) had a hidden input and an output layer. Solar irradiance, the number of days in a month and mean air temperature per day were the input factors, whereas the output gave the parameters of 24 h solar irradiance on the following day (i.e. at time $t + 1$). Air temperature and solar irradiance statistics from July 1st, 2008 to May 23rd, 2009 and from November 23rd, 2009 to January 24th, 2010 were used for the experimental work. The K-fold cross-validation method was implied for MLP forecaster validation. This cross-validation

Table 7
Comparison of different ANN hourly and monthly solar radiation prediction models.

Ref.	Prediction period Mth/Hrs.	ANN prediction error at max	Mapping No. ANN to empirical	Other models prediction error at max
Alam et al. (2009)	Mth	RMSE (%) 4.5 1.1 Min	1–1	RMSE (%) 37.4 4.0 Min
Şenkal and Kuleli (2009)	Mth	*R* 98.99 Max 84.51 Min RMS (%) 4.91 Max 0.08 Min	1–1	*R* 99.93 Max 96.84 Min RMS (%) 4.46 Max 0.89 Min
(Qin et al., 2011)	Mth	*R* 0.99 Max 0.89 Min RMSE (%) 1.85 Max 0.86 Min	1–2	*R* 0.99 Max Model 1 0.90 Min 0.99 Max Model 2 0.79 Min RMSE (%) 2.55 Max Model 1 0.83 Min 5.94 Max Model 2 0.73 Min
Ozgoren et al. (2012)	Mth	MAPE (%) 9.91 Max 5.34 Min *R* 0.99 Max 0.98 Min	1–1	MAPE (%) 16.17 8.25 Min *R* 0.9903 0.94 Min
Jiang (2009)	Mth	MPE (%) 5.43 Max −4.96 Min MBE (MJ/m^2) 0.94 Max −0.78 Min	1–6	MPE (%) 12.25 Max, −6.44 Min 11.55 Max, −6.98 Min 12.47 Max, −8.17 Min 13.37 Max, −5.95 Min 12.70 Max, −23.4 Min 12.74 Max, −22.1 Min MBE (MJ/m^2) 0.73 Max, −0.91 Min 0.72 Max, −0.98 Min 0.629 Max, −1.05 Min 0.711 Max, −0.86 Min 0.639 Max, −4.30 Min 0.642 Max, −4.14 Min
Benmouiza and Cheknane (2013)	Hrs	NRMSE 0.2003	1–1	NRMSE 0.3184
Chen et al. (2013)	Hrs	MAPE (%) 6.03–9.65	1–3	MAPE (%) 30 13.87–20.22 10.85–20.33

procedure was completed *K* times, with every one of the *K* subsets used precisely once through the test set. The outcomes illustrates that the correlation coefficient for sunny days was between 98% and 95%, indicating that the MLP predictor offered very satisfactory results, whereas it was also a suitable technique for cloudy conditions since the correlation coefficient found was between 92% and 95%. The analysis shows that the correlation of determination among measured and predicted power for 56 h is 0.90, so the results acquired are good.

Research work presented by Hasni et al. (2012) used back propagation neural network with the input of month, day, hour, temperature and relative humidity values. In this study, data was divided into parts to train the network, where the first part (2824 patterns from February 2 to May 31, 2011) was used for network training and the second part (651 patterns, from June 1 to 28, 2011) was used to test the trained network. The results show that the output for the predicted solar global radiation values is very close to the measured values for the period between February 2 and May 31, 2011. This shows good agreement between the prediction and measurements on an hourly basis with the proposed technique.

This study (Cambria et al., 2015a) was conducted by using five years of hourly solar radiation data collected in the Mediterranean site of Ajaccio, France. The competence of the model developed in this work with experimental data is satisfactory and often better than the adequacy obtained with empirical models discussed in this study. This ANN approach out-performs the traditional methods for this type of estimation and allows obtaining more reliable input data for modeling and optimizing solar energy systems.

The hourly global horizontal solar radiation was based on the combination of an unsupervised *k*-means clustering algorithm and artificial neural networks ANN in proposed work by Benmouiza and Cheknane (2013). In this work, two global horizontal solar radiation time series were selected for simulation purposes. Prediction accuracy evaluation was obtained by calculating the root mean square error (RMSE) and the normalized root mean square error (NRMSE). RMSE and NRMSE allowed for a term-by-term comparison of the actual difference between the predicted and measured values, and results were compared with the ARAMA empirical model. According to results, the forecasted series using the proposed method is virtually the same as the tested one with

RMSE of 60.24 Wh/m^2 and NRMSE of 0.1985, which are considered good forecast values compared to the ARMA model with NRMSE of 0.3078.

A model based on feed-forward Neural Network (FFN) with fuzzy logic for every hour in a day, i.e., from 08:00 to 18:00 is proposed (Chen et al., 2013). In this study, three sky conditions, sunny, rainy and cloudy, were classified for each hour. To find the sky condition for low, average or high the three usual average hourly temperature values were selected for each sky condition of every hour. The grouping procedure was enhanced and the reduced sky classes were found by implying fuzzy logic with ANN. Mean Absolute Percentage Error (MAPE) from the proposed system was 9.65%, which is lower than the other methods with respect to solar radiation forecasting. The results determine that the radiation forecast outcomes are much more precise and better when the proposed method is employed. The said techniques are summarized in Table 6.

In the above discussed monthly and hourly solar radiation prediction, few of studies compare the ANN model with empirical models. This comparison is carried out on the bases of prediction error such as RMSE, MAPE, MBE, NRMSE, R, and R^2. The subsequent Table 7 presents the comparison among different models in aforementioned studies. The comparison is presented on the basis of maximum and minimum prediction error produced by ANN and other empirical models.

Table 7 shows that, the proposed model in different aforementioned studies was compared with other empirical models and ANN proved better prediction ability.

4. Discussion and prospects

Solar radiation prediction methods examined in the current work are distinctive and provide valuable outcome for various circumstances. The models regarded as capable and convenient for hourly and monthly prediction are the feed-forward neural network, adaptive feed-forward neural network with fuzzy logic, back propagation and multilayer feed-forward neural network. A number of significant aspects identified in literature as well as shortcomings with solutions recommended in the present work are summed up subsequently.

The geographical and meteorological parameters used as input variables to ANN models for solar radiation prediction included sunshine length, maximum ambient temperature, relative humidity, latitude, longitude, day of the year, daily clear sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind velocity, atmospheric pressure, reference clearness index, mean diffuse radiation, mean beam radiation, month, extraterrestrial radiation, evaporation, and soil temperature. The defined prediction metrics for ANN models change with the influence of geographical meteorological variables, training algorithms and ANN architecture configuration. Thus, we can safely say that the correct choice of input parameters is essential to predict solar radiation with reliability and better accuracy.

The literature presented does not indicate any standard database for testing and evaluating how different systems can perform suitably. A database having the types of input parameters, the recording intervals of data, the number of training and test data and the error metrics in a standard way can be constructed for each time scale in solar radiation prediction.

The specifications containing information about total datasets, training sets, test sets and data recording intervals are not completely available in the literature studies. These specifications should be considered properly in future studies in order to evaluate prediction models properly.

The mean percentage error (MPE), mean bias error (MBE), root mean square error (RMSE) and correlation coefficient R^2 are widely used to compare the accuracy of proposed ANN models. Certain standard error prediction metrics are requisite for multiple model comparisons in performance assessment. The majority of research works employ their individual error metrics to yield solar radiation prediction outcomes. In literature, the most favored and frequently applied parameters to obtain straightforward, suitable evaluation are mean absolute error, as well as normalized and root mean square errors. These metrics can be commonly used for making a simple and acceptable evaluation.

In light of the presented literature, it seems that a number of sites do not have meteorological stations, whereby ANN models should be developed using the latitude, altitude, longitude and extraterrestrial radiation inputs for precise measurements. ANN has newly been initiated for predicting renewable energy resources, but additional work is necessary to increase solar radiation prediction accuracy pertaining to various seasons, climate change and poor weather, on different surfaces, e.g., tiled. Thus, the greatest advantages may be acquired from natural resources to supply increasingly reliable, efficient solar systems on the market.

5. Conclusion

This paper presents a systematic review of literature on predictive data mining techniques for solar radiation prediction and solar system development. Of the 373 initial papers located in well-known electronic research databases, 24 relevant papers were extracted and assessed accordingly. The finding in our research provides future dimensions to industry and research practitioners for further work on solar systems and solar radiation prediction.

ANN models are found to predict solar radiation accurately in different climatic conditions. This is due to the fact that this model can accept many input parameters as compared to empirical models that strengthen its reliability. In addition, it can also be concluded that ANN-based prediction offers greater accuracy as compared to empirical models, e.g. Table 7 shows prediction error is in range (less than 20%) and this could be very good in terms of solar radiation prediction. Therefore, ANN is much more demanding in the domain of renewable energy resource predication, such as solar radiation predication and solar system design. All things considered, adaptive neuro-fuzzy inference systems, neural networks and multilayer perceptron's enhance the prediction correctness in monthly and hourly solar radiation predictions, respectively. Furthermore, the study substantiates that ANN models predict solar radiation more accurately than statistical, conventional, linear, non- linear and fuzzy logic models. It is finally recommended that future studies on solar radiation prediction should consider the artificial neural network techniques in order to achieve better results.

As a result of this study, it can be said that adaptive neuro-fuzzy inference systems and neural networks increase the prediction accuracies in monthly and hourly solar radiation predictions respectively. It is determined that there is a need for further research on ANN and its applications. The promising results obtained from the use of ANN may help industry to benefit from the use of ANN. The information provided in this paper would be highly beneficial to the researchers working in the field of solar radiation prediction.

Acknowledgement

This work has been supported by High Impact Research Secretariat (HIR) at University of Malaya through the “Campus Network

Smart Grid System for Energy Security" Project (Under grant numbers: UM.C/HIR/MOHE/ENG/32 and H-16001-00-D000032).

References

Alam, Shah, Kaushik, S.C., Garg, S.N., 2009. Assessment of diffuse solar energy under general sky condition using artificial neural network. Appl. Energy 86 (4), 554–564.

Auer, Peter, Burgsteiner, Harald, Maass, Wolfgang, 2008. A learning rule for very simple universal approximators consisting of a single layer of perceptrons. Neural Netw. 21 (5), 786–795.

Behrang, M.A., Assareh, E., Ghanbarzadeh, A., Noghrehabadi, A.R., 2010. The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Sol. Energy 84 (8), 1468–1480.

Benmouiza, Khalil, Cheknane, Ali, 2013. Forecasting hourly global solar radiation using hybrid *k*-means and nonlinear autoregressive neural network models. Energy Convers. Manag. 75, 561–569.

Boehm, Matthias, Thomas, Oliver, 2013. Looking beyond the rim of one's teacup: a multidisciplinary literature review of product–service systems in information systems, business management, and engineering & design. J. Clean. Prod. 51, 245–260.

Brereton, Pearl, Kitchenham, Barbara A., Budgen, David, Turner, Mark, Khalil, Mohamed, 2007. Lessons from applying the systematic literature review process within the software engineering domain. J. Syst. Softw. 80 (4), 571–583.

Cambria, Erik, Fu, Jie, Bisio, Federica, Poria, Soujanya, 2015a. AffectiveSpace 2: Enabling Affective Intuition for Concept-Level Sentiment Analysis.

Cambria, Erik, Gastaldo, Paolo, Bisio, Federica, Zunino, Rodolfo, 2015b. An ELM-based model for affective analogical reasoning. Neurocomputing 149, 443–455.

Cetiner, Cuma, Halici, Fethi, Cacur, Hamit, Taymaz, Imdat, 2005. Generating hot water by solar energy and application of neural network. Appl. Therm. Eng. 25 (8), 1337–1348.

Chen, S.X., Gooi, H.B., Wang, M.Q., 2013. Solar radiation forecast based on fuzzy logic and neural networks. Renew. Energy 60, 195–201.

Colak, Ilhami, Sagiroglu, Seref, Demirtas, Mehmet, Yesilbudak, Mehmet, 2013. A data mining approach: analyzing wind speed and insolation period data in Turkey for installations of wind and solar power plants. Energy Convers. Manag. 65, 185–197. http://dx.doi.org/10.1016/j.enconman.2012.07.011.

Fayaz, H., Rahim, N.A., Saidur, R., Solangi, K.H., Niaz, H., Hossain, M.S., 2011. In: . Solar Energy Policy: Malaysia VS Developed Countries. 2011 IEEE First Conference on Clean Energy and Technology CET, pp. 374–378.

Hasni, Abdelhafid, Sehli, Abdelkrim, Draoui, Belkacem, Bassou, Abdesselam, Amieur, Belkacem, 2012. Estimating global solar radiation using artificial neural network and climate data in the south-western region of Algeria. Energy Proc. 18, 531–537.

He, Hongbo, Caudell, Thomas P., Menicucci, David F., Mammoli, Andrea A., 2012. Application of adaptive resonance theory neural networks to monitor solar hot water systems and detect existing or developing faults. Sol. Energy 86 (9), 2318–2333. http://dx.doi.org/10.1016/j.solener.2012.05.015.

He, Hongbo, Menicucci, David, Caudell, Thomas, Mammoli, Andrea, 2011. Real-time fault detection for solar hot water systems using adaptive resonance theory neural networks. In: Paper Presented at the Proceedings of ASME 2011, 5th International Conference on Energy Sustainability & 9th Fuel Cell Science, Engineering and Technology Conference, Washington DC, ESFuel-Cell2011-54885.

Hepbasli, Arif, Alsuhaibani, Zeyad, 2011. A key review on present status and future directions of solar energy studies and applications in Saudi Arabia. Renew. Sustain. Energy Rev. 15 (9), 5021–5050. http://dx.doi.org/10.1016/j.rser.2011.07.052.

IEA, 2013. IEA: Global Solar Capacity Nearing 100GW Milestone. Retrieved 21.10.13, from: http://www.pv-tech.org/news/report_global_capacity_reaches_almost_90gw.

Jiang, Yingni, 2008. Prediction of monthly mean daily diffuse solar radiation using artificial neural networks and comparison with other empirical models. Energy Policy 36 (10), 3833–3837.

Jiang, Yingni, 2009. Computation of monthly mean daily global solar radiation in China using artificial neural networks and comparison with other empirical models. Energy 34 (9), 1276–1283.

Journée, Michel, Bertrand, Cédric, 2010. Improving the spatio-temporal distribution of surface solar radiation data by merging ground and satellite measurements. Rem. Sens. Environ. 114 (11), 2692–2704.

Kalogirou, S.A., Mathioulakis, E., Belessiotis, V., 2014. Artificial neural networks for the performance prediction of large solar systems. Renew. Energy 63, 90–97. http://dx.doi.org/10.1016/j.renene.2013.08.049.

Kalogirou, Soteris, Lalot, Sylvain, Florides, Georgios, Desmet, Bernard, 2008. Development of a neural network-based fault diagnostic system for solar thermal applications. Sol. Energy 82 (2), 164–172.

Karatepe, Engin, Boztepe, Mutlu, Colak, Metin, 2006. Neural network based solar cell model. Energy Convers. Manag. 47 (9), 1159–1178.

Keele, Staffs, 2007. Guidelines for Performing Systematic Literature Reviews in Software Engineering: Technical Report (EBSE Technical Report EBSE-2007-01).

Khoshnevisan, Benyamin, Rafiee, Shahin, Omid, Mahmoud, Mousazadeh, Hossein, Clark, Sean, 2014. Environmental impact assessment of tomato and cucumber cultivation in greenhouses using life cycle assessment and adaptive neuro-fuzzy inference system. J. Clean. Prod. 73, 183–192.

Khoshnevisan, Benyamin, Rafiee, Shahin, Omid, Mahmoud, Mousazadeh, Hossein, Sefeedpari, Paria, 2013. Prognostication of environmental indices in potato production using artificial neural networks. J. Clean. Prod. 52, 402–409.

Koca, Ahmet, Oztop, Hakan F., Varol, Yasin, Koca, Gonca Ozmen, 2011. Estimation of solar radiation using artificial neural networks with different input parameters for Mediterranean region of Anatolia in Turkey. Expert Syst. Appl. 38 (7), 8756–8762.

Köhler, Jonathan, Schade, Wolfgang, Leduc, Guillaume, Wiesenthal, Tobias, Schade, Burkhard, Espinoza, Luis Tercero, 2013. Leaving fossil fuels behind? An innovation system analysis of low carbon cars. J. Clean. Prod. 48, 176–186.

Koroneos, Christopher J., Nanaki, Evanthia A., 2012. Life cycle environmental impact assessment of a solar water heater. J. Clean. Prod. 37, 154–161.

Kusama, Hitoshi, Konishi, Yoshinari, Sugihara, Hideki, 2007. Data mining assisted by theoretical calculations for improving dye-sensitized solar cell performance. Sol. Energy Mater. Sol. Cells 91 (1), 76–78.

Laidi, Maamar, Hanini, Salah, 2013. Optimal solar COP prediction of a solar-assisted adsorption refrigeration system working with activated carbon/methanol as working pairs using direct and inverse artificial neural network. Int. J. Refrigeration 36 (1), 247–257. http://dx.doi.org/10.1016/j.ijrefrig.2012.09.016.

Landis, J.R., Koch, G.G., 1977. The measurement of observer agreement for categorica data. Biometrics 159–174.

Liu, Zhe, Wang, Xiu Chen, 2013. Manufacture and performance evaluation of solar garment. J. Clean. Prod. 42, 96–102.

Luo, Qi, 2008. Advancing knowledge discovery and data mining. In: Paper Presented at the Knowledge Discovery and Data Mining, 2008. WKDD 2008. First International Workshop on.

Martí, Pau, Gasque, María, 2011. Improvement of temperature-based ANN models for solar radiation estimation through exogenous data assistance. Energy Convers. Manag. 52 (2), 990–1003.

Mellit, Adel, Pavan, Alessandro Massi, 2010. A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy. Sol. Energy 84 (5), 807–821.

Mohanraj, M., Jayaraj, S., Muraleedharan, C., 2009. Performance prediction of a direct expansion solar assisted heat pump using artificial neural networks. Appl. Energy 86 (9), 1442–1449. http://dx.doi.org/10.1016/j.apenergy.2009.01.001.

Nixon, J.D., Dey, P.K., Davies, P.A., 2013. Design of a novel solar thermal collector using a multi-criteria decision-making methodology. J. Clean. Prod. 59, 150–159.

Notton, Gilles, Paoli, Christophe, Vasileva, Siyana, Nivet, Marie Laure, Canaletti, Jean-Louis, Cristofari, Christian, 2012. Estimation of hourly global solar irradiation on tilted planes from horizontal one using artificial neural networks. Energy 39 (1), 166–179.

Ozgoren, Muammer, Bilgili, Mehmet, Sahin, Besir, 2012. Estimation of global solar radiation using ANN over Turkey. Expert Syst. Appl. 39 (5), 5043–5051.

Porrazzo, R., Cipollina, A., Galluzzo, M., Micale, G., 2013. A neural network-based optimizing control system for a seawater-desalination solar-powered membrane distillation unit. Comput. Chem. Eng. 54, 79–96. http://dx.doi.org/10.1016/j.compchemeng.2013.03.015.

Qazi, Atika, Fayaz, H., Raj, Ram Gopal, 2014. Discourse on data mining applications to design renewable energy systems. In: International Conference on Advances in Engineering and Technology (ICAET'2014) March 29–30, 2014 Singapore, pp. 418–420.

Qin, Jun, Chen, Zhuoqi, Yang, Kun, Liang, Shunlin, Tang, Wenjun, 2011. Estimation of monthly-mean daily global solar radiation based on MODIS and TRMM products. Appl. Energy 88 (7), 2480–2489.

Rosiek, S., Batlles, F.J., 2010. Modelling a solar-assisted air-conditioning system installed in CIESOL building using an artificial neural network. Renew. Energy 35 (12), 2894–2901. http://dx.doi.org/10.1016/j.renene.2010.04.018.

Rupnik, Rok, Jaklič, Jurij, 2009. The deployment of data mining into operational business processes.

Sadoyan, Hovhannes, Zakarian, Armen, Mohanty, Pravansu, 2006. Data mining algorithm for manufacturing process control. Int. J. Adv. Manuf. Technol. 28 (3–4), 342–350.

Şenkal, Ozan, Kuleli, Tuncay, 2009. Estimation of solar radiation over Turkey using artificial neural network and satellite data. Appl. Energy 86 (7), 1222–1228.

Seuring, Stefan, Müller, Martin, 2008. From a literature review to a conceptual framework for sustainable supply chain management. J. Clean. Prod. 16 (15), 1699–1710.

Souliotis, M., Kalogirou, S., Tripanagnostopoulos, Y., 2009. Modelling of an ICS solar water heater using artificial neural networks and TRNSYS. Renew. Energy 34 (5), 1333–1339. http://dx.doi.org/10.1016/j.renene.2008.09.007.

Sözen, Adnan, Arcaklioğlu, Erol, Özalp, Mehmet, Kanit, E. Galip, 2004. Use of artificial neural networks for mapping of solar potential in Turkey. Appl. Energy 77 (3), 273–286.

Stechemesser, Kristin, Guenther, Edeltraud, 2012. Carbon accounting: a systematic literature review. J. Clean. Prod. 36, 17–38.

Suehrcke, H., McCormick, P.G., 1992. A performance prediction method for solar energy systems. Sol. Energy 48 (3), 169–175.

White, Adrian, Schmidt, Katja, 2005. Systematic literature reviews. Complem. Ther. Med. 13 (1), 54–60.

Yuan, Xueliang, Zuo, Jian, Huisingh, Donald, 2015. Social acceptance of wind power: a case study of Shandong Province, China. J. Clean. Prod. 168–178.