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A Comparative Assessment of Predicting Daily Solar Radiation Using Bat Neural Network (BNN), Generalized Regression Neural Network (GRNN), and Neuro-Fuzzy (NF) System: A Case Study

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Abstract: Highly accurate estimating of daily solar radiation by developing an intelligent and robust model has been a subject of prominent concern for many researchers in the past few years. The precise prediction of solar radiation is of great interest and importance to improve the incorporation of solar power plants. In this study, a novel multilayer framework for a particular combination of the bat algorithm (BA) and neural networks (NN) is proposed, which is called bat neural network (BNN), aimed at predicting daily solar radiation over Iran. For appraising the performance of the proposed BNN, daily solar radiation data from four cities of Iran including Jask, Kermanshah, Ramsar, and Tehran are analyzed. The results indicate that among the tested models, BNN gains the best performance in the prediction of daily solar radiation. Among various soft computing approaches, the BA, which is inspired by the nature of microbats' behaviour, has a significant impact on the optimization of this study.

Keywords: solar radiation; prediction; artificial neural network; data mining; bat algorithm

1. Introduction

For decades, energy-related problems have been major worldwide concerns [1,2]. These days, environmental concerns and social pressures are going to change the earth to a more sustainable planet [1]. From the energy supply perspective, it is important to manage and guarantee the energy security and supply [2], especially via the diversification of supply and new green technology development. Renewable energies are considered to be clean since they do not have a negative impact on environment [3]. Nonrenewable energies such as fossil fuels have provided almost 80% of the global energy demand in recent years [4]. Nowadays, many environmental issues are caused by the tremendous utilization of hazardous fossil fuel resources. Global warming and greenhouse gas emissions have led to a global exploration for alternative energy resources to meet the ongoing worldwide energy demand. In this case, solar energy is a promising alternative energy resource owing to abundance, cleanness, and cost-effectiveness characteristics, which can generate electricity and heat without any environmental degradation [5]. Nevertheless, solar energy exposes a fluctuating generation profile, unlike conventional power generation plants, which can operate unceasingly. Because of the inherent cyclical and time-varying nature of solar energy, this leads to limitations of the stability and trustworthiness of solar power grid systems [6]. In order to have a stable energy supply, it is necessary to integrate solar plants with other backup energy supporters for the times that solar power production drops (mainly due to cloudy weather). As a decisive factor, the precise estimation of solar radiation could be of great interest and importance to improve the incorporation of solar power plants [7]. The prediction of solar radiation is generally applied for an extensive range of technical applications including the solar radiation data requirements of agricultural, architectural, biological, industrial, and medical projects. For instance, the prediction of daily solar radiation in the cases related to solar power plants locations is important and determinative. The importance and preference of the time scale (daily, monthly, hourly, or by minute) as one of the classifications of solar radiation estimation can vary according to the application that the user aims to employ. Interestingly, the daily solar radiation data is a critical factor for site selection, designs, and for the feasibility assessment of solar power plant projects, in particular for the areas with no measured solar radiation data [8].

Recently, many developing countries have shifted toward implementing renewables which aim at combating global warming, and also to reduce costs [9]. Since solar radiation prediction is a challenging issue in the renewable energy context [10] there are a lot of methodologies and approaches in solving the mentioned issue and the related problems. In this regard, computational intelligence methods like Artificial Neural Networks (ANNs) are modern paradigms to conquer the complex prediction problems [11–13]. Recently, numerous attempts used ANNs to deal with daily solar radiation prediction problems [14–16]. In an ANN, the weight training is expressed as an error function minimization problem. One approach to achieving an optimum neural network is to minimize the mean square error between the target and real outputs for all training datasets by modifying the weight of connections in an iterative manner. Gradient descent is the base of most training algorithms, including the back-propagation (BP) algorithm. One drawback of the BP algorithm is getting caught in a local minimum of error function trap. In other words, if the error function is nondifferentiable and/or multimodal, it is incapable of finding a global minimums [17]. Concisely, the performance of an ANN is based on the weights of connections and also the structure of the network. Therefore, to achieve the best results, several optimizing algorithms have been implemented for the process of ANN model selection [18]. A new algorithm which has good performance for solving many optimization issues in diverse areas is the bat algorithm (BA) [19]. The algorithm is a powerful and reliable tool for addressing a broad range of global optimization problems [20]. The BA is a population-based metaheuristic algorithm which is founded on the echolocation or biosonar characteristics of microbats [21]. The BA benefits from combining a population-based algorithm with a local search [18]. Furthermore, similar to Yang's algorithms of cuckoo search [22] and firefly [23], the BA integrates the benefits of available algorithms, particularly harmony search (HS), and particle swarm optimization (PSO); therefore, the BA has enough potential to perform better than the other algorithms. In this study, a multilayer architecture and the BA were used to optimize the weights parameters of an ANN and propose the BNN model aimed at prediction of daily solar radiation. The paper seeks to answer a common renewable energy problem (the estimation of solar radiation) while proposing a novel multilayer intelligent process. To prove the model's robustness, the proposed architecture has been applied to various datasets with different historical patterns from different geographical regions (weather conditions).

The next section offers a discussion of literature reviews. The methodology is brought forward in Section 3. Experimental results are illustrated in Section 4. Finally, concluding remarks are presented in Section 5.

2. Literature Review

Today, enormous attempts have been concentrated on artificial intelligence (AI) models for forecasting problems; meanwhile, applying AI models or an integration of various models have become an usual approach to increase forecasting precision [24,25]. Therefore, the literature on this topic has grown considerably. Training an ANN is a complicated task that has a straightforward impact on the outcomes. Using the optimization techniques in ANN model training can lead to effective ANN models [14]. Consequently, over the past few years, many successful research studies were conducted which include applied metaheuristic and intelligent algorithms (e.g., the genetic algorithm) [17,26] introduced a metaheuristic bat-inspired algorithm and illustrated that its performance was better than robust algorithms like genetic algorithm (GA) and particle swarm optimization (PSO) in their standard versions [17]. Ikeda and Ooka used the self-adaptive learning bat algorithm (SLBA) to optimize an operating schedule of energy systems and compared it with other four metaheuristics. They compared the obtained results of these metaheuristics with dynamic programming optimization method [27]. Karri and Jena proposed a hybrid algorithm named BA-LBG, in which a BA was initialized with the solution of the Linde–Buzo–Gray (LBG) algorithm. The LBG is a conventional method for vector quantization (VQ) which generates a local optimal codebook [28]. Gao et al. employed different bat algorithms for searching for a target in sequential images. In the proposed a BA-based tracking architecture, the sensitivity and modification of the parameters in the BA were studied experimentally [20]. Rahimi et al. used a self-adaptive learning based on the BA for the case of chaotic systems aimed at estimating both offline and online parameters of the system [29]. A discrete version of the BAs was presented by Osaba et al. to solve the well-known "traveling salesman" problem. This study claimed that the proposed model improves the basic structure of the classic BA [21]. The classical bat optimization method proposed by Yang [26] needs to be able to assess and keep velocities from earlier iterations to compute new solutions. Wood proposed a procedure to remove this requirement; thereby the computational speed increases without adversely affecting the performance of the algorithm as an effective optimizer [30]. Furthermore, Topal and Altun presented a dynamic virtual bat algorithm (DVBA) to manage the wavelength and frequency of the sound waves emitted by the bats when hunting by using two bats: explorer and exploiter [19]. Sudabattula and Kowsalya used the BA to optimize the allocation of solar-based distributed generators as well as minimizing power loss in a radial distribution system [31]. Hafezi et al. introduced a multiagent-based structure which used a bat algorithm as the tuning agent for adjusting the ANN's weights, which caused the obtaining of significant results [32]. Jaddi et al. applied the original version of the BA and two modified versions thereof which they developed to improve the exploiting and exploring feasibilities of the algorithm. Furthermore, during the training phase, various versions of their BA algorithm was included to manage the ANN's structure selection and the value of connection weights and biases. They used six classifications and two time-series datasets to evaluate their proposed methods [33]. Regarding an optimum placement and sizing of the distributed generations in the distribution systems, Yammani et al. offered an innovative multi-objective algorithm which used a modified BA. They investigated some primary criteria in the distribution systems (i.e., power losses, cost and voltage deviation) in various contexts [34]. At the end of this section, we summarize the previous research studies on solar radiation forecasting with different algorithms in other regions, especially in Iran. At first, the oldest soft computing technique, adaptive neuro-fuzzy inference system (ANFIS), was utilized to forecast solar radiation for 21 years from 1987 to 2007 from a series of measured meteorological data on one site only in Oshodi in Nigeria [7]. Another ANFIS with a different structure was adopted to forecast the daily global solar radiation by day of the year as a single input for the Iranian city of Tabass [35]. A support vector machine with radial and polynomial basis function was proposed to predict the daily horizontal global solar radiation (HGSR) on a horizontal surface and sunshine hours for Isfahan for the period of 1985–1991 and 1981–2003 [36]. The same method was applied for global solar radiation (GSR) for a seven-year period (1994–2000) from the solar station in Tehran, Iran [37]. Wavelet transform and a support vector machine were used for forecasting the horizontal global solar irradiation. The following long-term data were provided by the Iranian Meteorological Organization (IMO) for the city of Bandar Abbas in the south of Iran from 1992 to 2005: sunshine hours, average, minimum and maximum air temperature, daily global solar radiation on a horizontal surface, water vapor pressure, and relative humidity [38]. On the other hand, an SVM with the firefly algorithm was applied for the forecasting of horizontal global solar radiation in the three sites of Iseyin, Maiduguri, and Jos in various districts of Nigeria during 21 years from 1987–2007 [7]. A kernel extreme learning machine was developed to forecast the daily horizontal global solar radiation within the lowest to highest ambient temperature ranges [39].

3. Methodology

To achieve reasonable and accurate results, this paper proposed a multilayered methodology attempting to integrate the benefits of pattern recognition using machine learning algorithms and knowledge discovery using data mining techniques. The proposed multilayered methodology is conceptually presented in Figure 1:

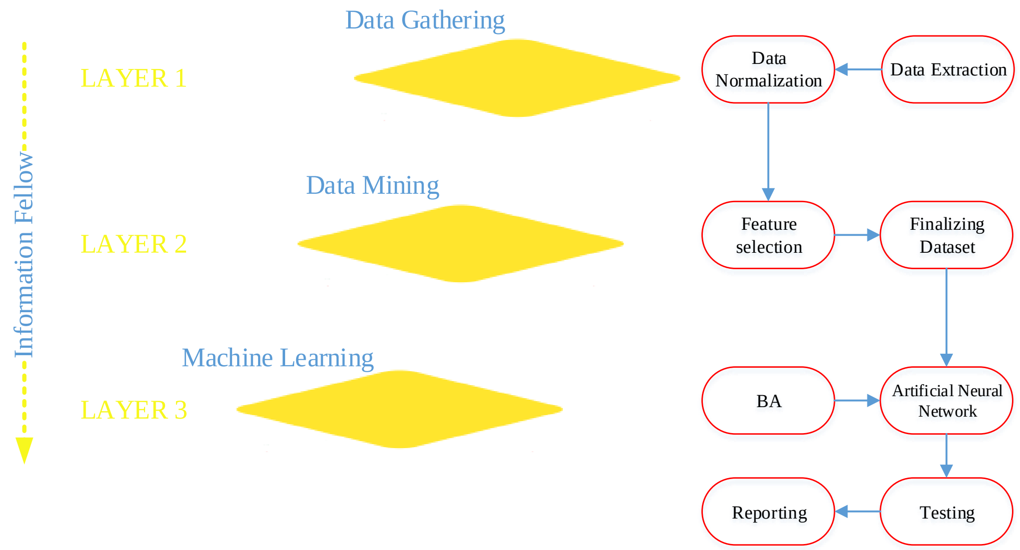

Figure 1. The conceptual framework of the proposed methodology. BA: Bat Algorithm; ANN: artificial neural network.

3.1. Layer 1: Data Gathering

The starting point of the proposed methodology is data gathering, aimed at providing raw, reliable, and relevant data. The second step is data normalization. The dataset consists of different features with different scales. To estimate the relevance and strength of the relation between each feature and the target variable (here the goal is to predict daily solar radiation values), there is a vital need for normalizing data vectors corresponding to each feature. The following equation is used to normalize the existing dataset:

$$z_{ij} = \frac{x_i - \min(X_i)}{\max(X_i) - \min(X_i)} \tag{1}$$

where $X = (x_1, x_2, .., x_n)$ and z_{ij} is the i^{th} normalized data for the j^{th} feature.

3.2. Layer 2: Data Mining

Knowledge discovery in databases is comprised of five stages: data selection, preprocessing, transformation, data mining, and interpretation/evaluation. In this context, data mining is the procedure of finding fascinating patterns in massive amounts of data and extracting knowledge. In this matter, the principal dimensions are data, knowledge, applications, and technologies [40].

This layer is aimed at presenting the most relevant features and putting useless features aside without missing valuable solution space. This step also is known as "data reduction". Apparently, developed models would operate faster when the input dataset contains lower dimensions. Furthermore, a feature selection process guarantees the detection of the most relevant features which can prevent useless or irrelevant data from deflecting the prediction model.

A significant problem in knowledge discovery is that of feature subset selection; not merely for the intuition obtained from discovering related modeling variables, but also for the comprehensibility, scalability, possibility, and accuracy enhancement of the subsequent models [41]. A principal component analysis (PCA) algorithm was implemented to select relevant features. Principal components are linear combinations of observed variables ordered based on a criterion of pertinent information and is represented by their variance [42]. Weka, as an eminent machine learning software package for data mining, is applied to determine the final features among ten available features.

3.3. Layer 3: Machine Learning

An Artificial Intelligence (AI) approach is used in this research to recognize hidden patterns of the input data, to predict future trends and fluctuations. Thus, selected features are used as the input vectors for an ANN which is adjusted for solar radiation prediction problems. The ANN is a brain-inspired class of computational procedures aimed at imitating the way of human learning. The computing units of a neural network are called neurons.

An ANN consists of characteristics which are listed below as shown in Figure 2:

1. The layers of input.
2. The hidden layers.
3. The interconnection among various layers.
4. The learning procedure to optimize and update interconnections weights.
5. The transformer function aimed at delivering weighted inputs to target outputs.
6. The quantity of the neurons performing in each layer.
7. The output layers.

An ANN can be trained in order to adjust the weight matrix, w_{ij}, to construct a more precise network and minimize the performance (lost) function [32]. Consequently, the performance of the network depends on the learning algorithms. Numerous successful research studies have applied metaheuristic and intelligent algorithms, like the genetic algorithm, to train ANNs [43].

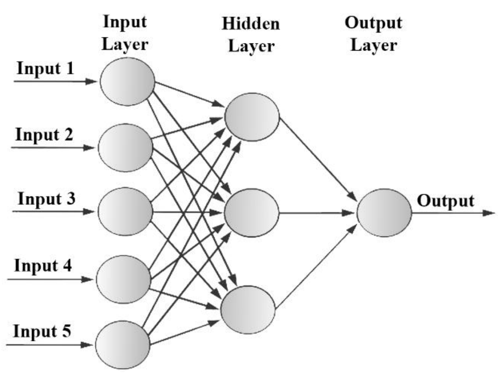

Figure 2. Basic parameters of an ANN.

Typically, ANN-based material design approaches are intended to train the system by learning-based methods, where some data are generated according to the empirical surveys [44]. Yang developed the BA based on the biological behavior of bats in nature [26]. In this research, the BA was applied to optimize the ANN weights. Figure 3 shows how the BA works.

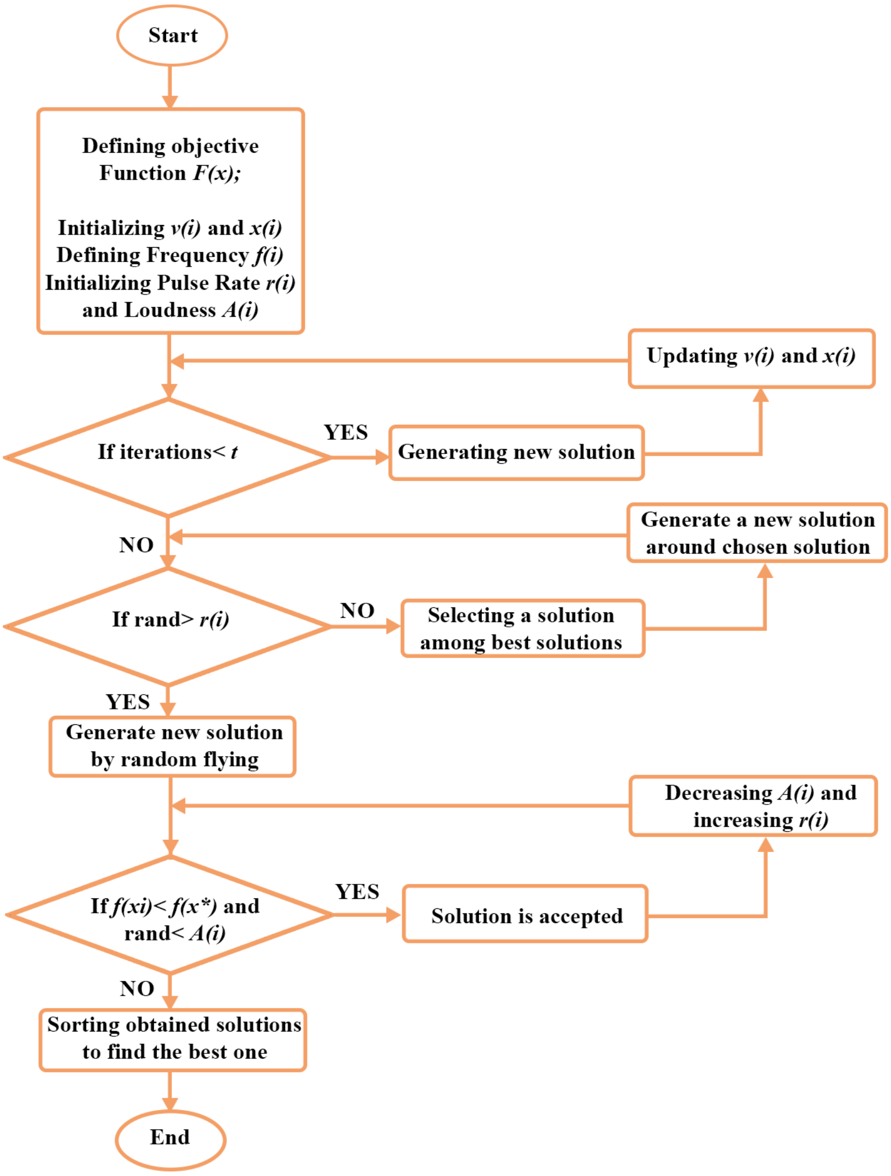

Figure 3. The general procedure of the BA.

Figure 3 illustrates that three parameters must be defined: s_i, which is representative of position/solution; v_i, which refers to the velocity and dimension of the searching space; and in the next stage, the initial frequency has to be determined by the following equation:

$$f = f_{min} + (f_{max} - f_{min})\beta \tag{2}$$

where $\beta \in [0, 1]$ denotes a random vector derived from uniform distribution and f_{min} and f_{max} stand for predefined parameters that vary depending on the problem. Then, s_i and v_i must be updated using the following equations:

$$v_i^t = v_i^{t-1} + (x_i^t - s_*)f_i \tag{3}$$

$$s_i^t = s_i^{t-1} + v_i^t \tag{4}$$

Here, s_* represents the best global solution at the current state/iteration. A random walk procedure is implemented to create a new solution:

$$s_{new} = s_{old} + \varepsilon A^t \tag{5}$$

where ε denotes a randomly created value in the range of [−1,1] and A^t specifies the mean loudness value at the current iteration. A_i and r_i stand for loudness and pulse rate, respectively. These parameters update at each stage by means of the following equations:

$$A_i^{t+1} = \propto A_i \tag{6}$$

$$r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)] \tag{7}$$

Referring to bats' behavior in nature, loudness A_i usually decreases and pulse rate r_i usually increases one the bat reaches its target, so $\propto \in (0,1)$ and $\gamma > 0$ are constant predefined values. Also, when $t \to \infty$:

$$A_i^t \to 0 \text{ and } r_i^t \to r_i^0 \tag{8}$$

4. Experimental Results

4.1. Data

Daily solar radiation data was employed to run a prediction problem in order to appraise the performance of the suggested approach. Due to the availability limitations, four cities consisting of Jask, Kermanshah, Ramsar, and Tehran (the capital of the country) were nominated to provide input data. Figure 4 illustrates the geographical distribution of the targeted cities. Four datasets, referring to the four case studies/cities, are initialized, consisting of available historical data for several days.

Moreover, the variations of input data are illustrated in Figure 5 for each case. Overall, 85% of the input data was applied as the training data of the model, and the remaining 15% was employed to assess the performance of the models.

Figure 4. Geographical distribution of the targeted cities.

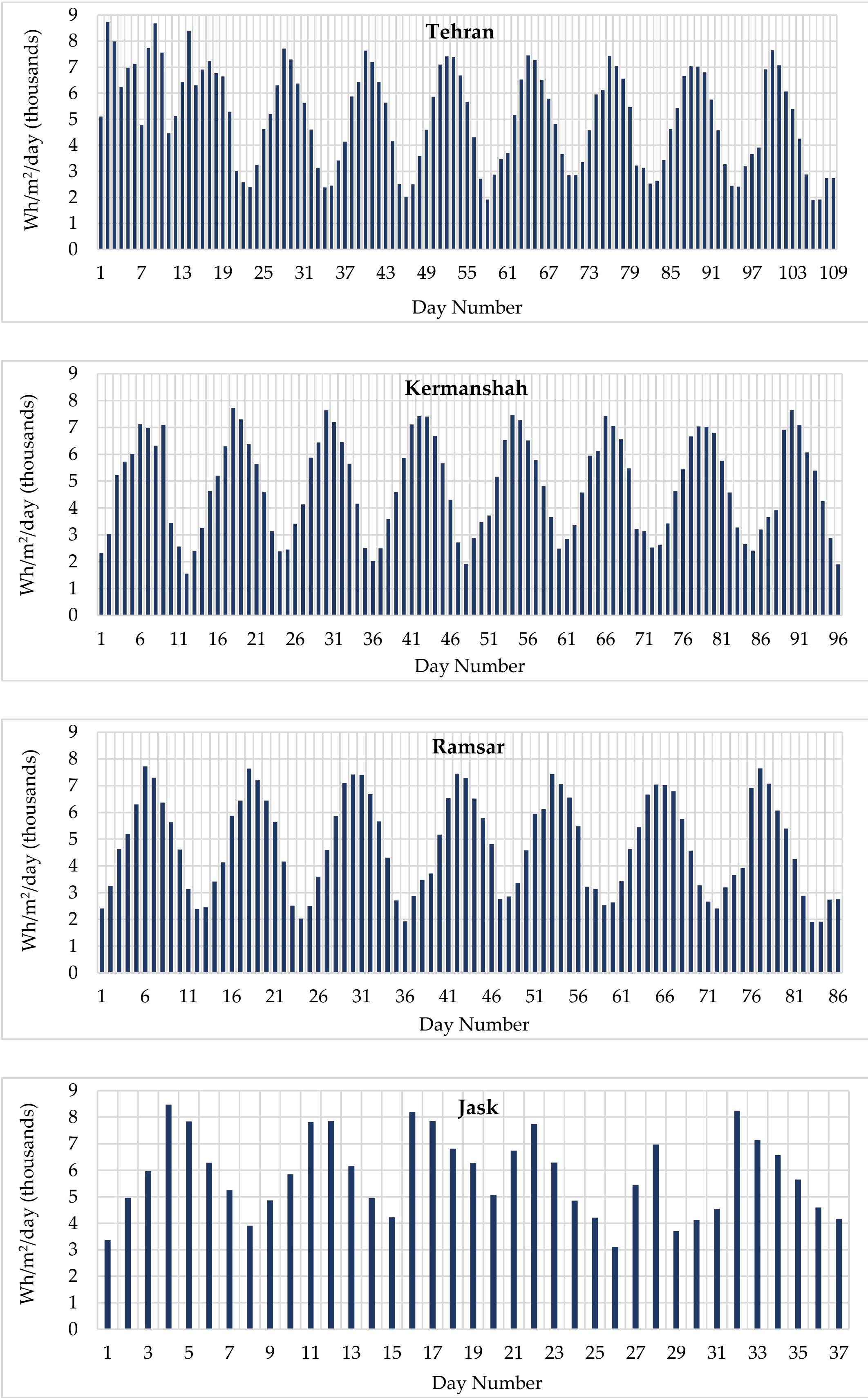

Figure 5. Input data for the four selected cities.

4.2. Model Implementation

The performance of the BNN was compared with two popular soft computing methods: the generalized regression neural network (GRNN) and the ANFIS.

The ANFIS method was firstly presented by Jang in 1993 [45] and can be described as a supervised learning network with a multilayer feed-forward structure which models the given training dataset using the Takagi–Sugeno system.

The ANFIS applies two different phases: The first phase is called the backward pass, aimed at optimizing the premise parameters of the fuzzy membership function used as input in layers one to three. The second one is the forward pass, which tries to optimize the resultant parameters in layers four and five [46].

The GRNN was originally presented by Specht in 1991 [47]. As a meta-modeling method, the GRNN holds various benefits. Based on the nonparametric regression, GRNN is formed based on the sampled data, implements the Parzen nonparametric prediction, and the output of the network is computed according to the maximum probability principle. Hence, it holds a great capability in nonlinear estimation. Moreover, the training process using GRNN is more beneficial and fascinating owing to the approximation facility and learning quickness in comparison with the radial basis neural networks [48].

It is worth to note that the smoothing factor is not remarkably sensitive to its setting [49]. The small sensitivity of smoothing factor serves as ease of the optimum selection of this parameter [50]. In the GRNN method, every training sample is regarded as a cluster. The GRNN commence to compute the Euclidean distance between the input and every training sample, as the new inputs are fed to the GRNN to estimate the output.

The current paper is aimed at providing a precise prediction, so the provided data in the prior phase was applied as input data for the first layer. Table 1 tabulated the main features and selected ones by PCA.

Table 1. Feature's descriptions.

Number#	Feature	Description	Selected
1	Fr1	Sunshine	Yes
2	Fr2	Mean Daily Temperature	Yes
3	Fr3	Mean Wind Speed	Yes
4	Fr4	Mean Humidity	Yes
5	Fr5	RRR	Yes
6	Fr6	Mean QFE	No
7	Fr7	Mean Dew	No
8	Fr8	Latitude	No
9	Fr9	Elevation	No
10	Fr10	Longitude	No

Note: RRR: broadband solar radiation; QFE: Atmospheric pressure at field elevation.

PCA is known as a popular dimension reduction tool used for both supervised and unsupervised problems [51–53]. As a statistical technique, PCA is implemented to educe the information from a multivariate dataset. The process starts with recognizing the principal component variables that are linear combinations of the original variables, where the datasets are prioritized based on the maximum variability; in other words, the original dataset with the largest possible variability is characterized by the first principal component [54]. Here, we used Weka software to implement the feature selection procedure using the PCA technique.

One hidden layer was selected to perform in a three-layer architecture. Furthermore, according to the functional testing results, a hidden layer with six neurons returns the best results in comparison to other neuron numbers. Results for different neurons are presented in Figure 6. Based on the results, a 5–6–1 architecture is preferred as the optimum structure.

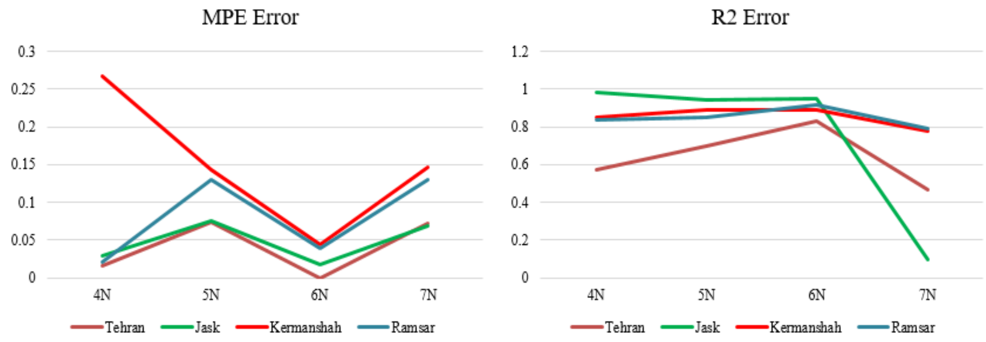

Figure 6. The forecasting results for different numbers of neurons.

In this study, various characteristics of the parameters (dissimilar numeric values) have been verified separately for all the intelligent models, and accurate values were achieved, with the aim of satisfying the proper design (best values of parameters) that makes the minimum error. The appropriate architectures for the benchmark models which had the minimum mean squared error among all of the other architectures are presented in Table 2. The optimum values were achieved by means of trial-and-error method. Parameters in Table 2 define the characteristics for each competitive model (for more information, see references mentioned previously in Section 4.2).

Table 2. Parameters of the models.

Model	Parameters
GRNN	spread = 0.2
ANFIS	FIS Generation Approach: Subtractive Clustering Influence Radius = 0.55 Maximum Number of Epochs = 100 Error Goal = 0 Step Size Increasing = 1.1
The proposed BNN	Number of Neurons = 6 Architecture of Neural Network: (5-6-1) Population Size = 5 Number of Generations = 5 $F_{min} = 0$ $F_{max} = 1$ Lambda = 1.5 Alpha = 0.5

To analyze the sufficiency of the developed BNN, GRNN, and ANFIS, the forecasted values are depicted versus the real data for each considered station. Figures 7–10 represent the scatter plots of the estimated solar radiation versus the real data of the testing dataset for each station.

Figure 11 indicates the performance of the BNN with GRNN and ANFIS based on the mean absolute error (MAE) measure. The results were gathered according to the best values of parameters for each model and dataset. According to Figure 11, the BNN shows a better performance than ANFIS and GRNN.

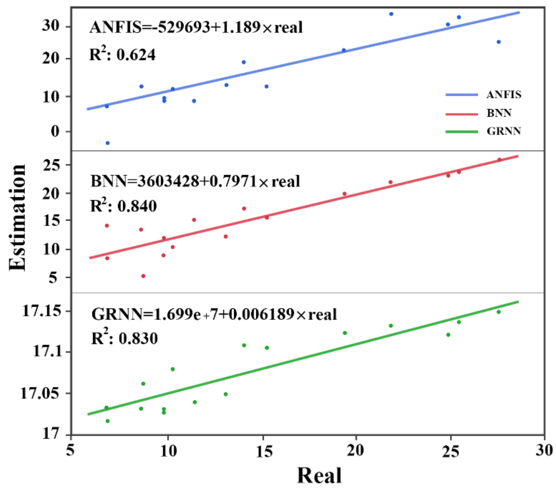

Figure 7. Comparison of estimated value of models and real data for test data of Tehran (MJ/M^2/day).

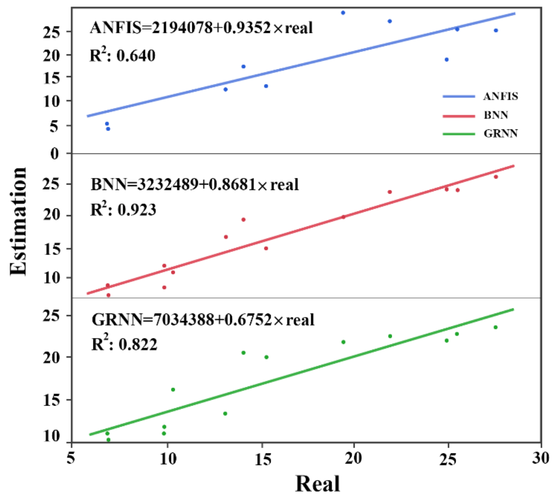

Figure 8. Comparison of estimated value of models and real data for test data of Ramsar (MJ/M^2/day).

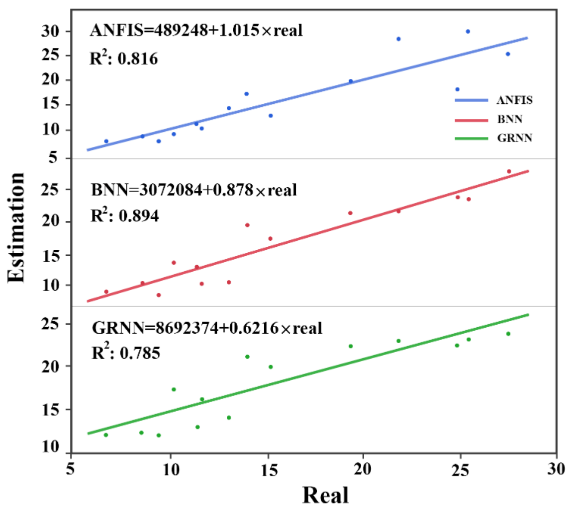

Figure 9. Comparison of estimated value of models and real data for test data of Kermanshah (MJ/M^2/day).

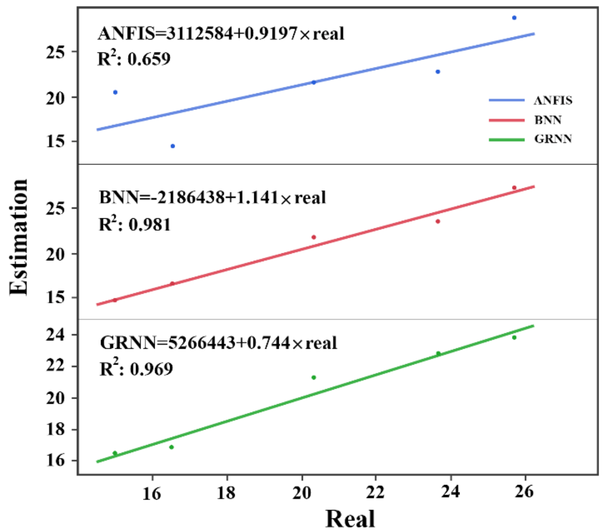

Figure 10. Comparison of estimated value of models and real data for test data of Jask (MJ/M^2/day).

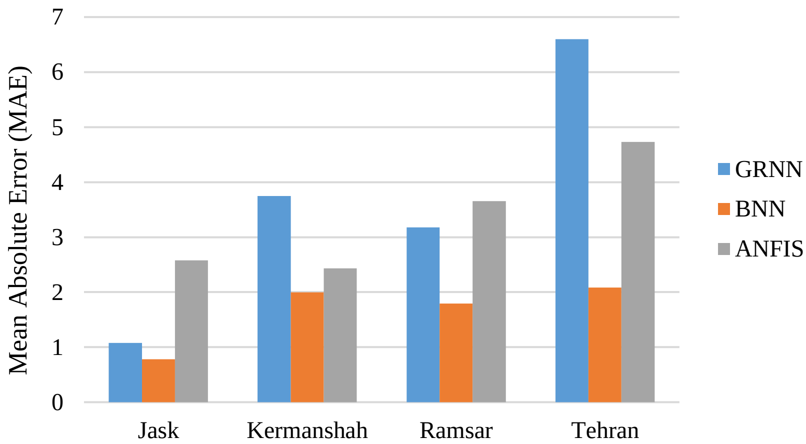

Figure 11. Comparison of the performance of the BNN with GRNN and ANFIS (MJ/M^2/day).

5. Conclusions

The accuracy of solar radiation estimation is vital for solar power plants. Among various soft computing approaches, the BA, which is inspired by the nature of microbats' behaviour, has a significant impact on optimization-oriented research studies. In this research, regarding the solar radiation forecasting, it is proposed a multilayer framework which benefits from an appropriate combination of the BA and ANN, known as the BNN. To assess the prediction precision of the considered framework, four cities of Iran were selected; 85 percent of the input data was applied as the training set, and the remaining 15% was employed to evaluate the performance of the proposed models. Based on the experimental test, in a three-layer architecture, an ANN with six neurons in its hidden layer performs better in comparison with other numbers of neurons. Ultimately, the optimum structure for the ANN which produces the best results is a 5–6–1 architecture. Based on the MAE and R-squared error (R^2) as two evaluation criteria, the BNN model was quite promising. For example, the MAE values of the BNN model were almost a third of the values of the ANFIS model in Jask and Tehran cities. Similarly, in Kermanshah and Ramsar cities, the MAE values of the BNN model gained almost half of the MAE values of the GRNN model. Furthermore, for the nominated cities, the values of R^2 of the BNN model were better than the other models. In Jask city, the value of R^2 of the BNN model was 0.981. Therefore, the BNN possessed a better performance than ANFIS and GRNN.

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