

Solar Radiation Prediction using Ant Colony Optimization and Artificial Neural Network

Md. Shahid Iqbal, Md. Monirul Kabir, Amit Shaha Surja, and Abdur Rouf

Abstract — This paper proposes a Solar Radiation Prediction Model employing Ant Colony Optimization (ACO) and Artificial Neural Network (ANN), named as SRPM. SRPM aims to incorporate the Feature Selection (FS) technique in the ANN training with the guidance of hybridizing ACO. The main reason behind using FS technique is, it can provide an improved solution from a particular problem by identifying the most salient features from the available feature set. In SRPM, the hybridizing ACO search technique utilizes the information gathered from the correlation among the features and the result of ANN training. To assist the ACO search, pheromone updating technique and measurement of heuristic information have been performed by two particular sets of rules. Thus, SRPM utilizes the benefits of using the wrapper and filter approaches in selecting the salient features during SRP task. The combination eventually creates an equipoise between exploration and exploitation of ants in the way of searching as well as strengthening the capability of global search of ACO for obtaining well qualified solution in SRPM. To evaluate the executive efficiency of SRPM, data samples were collected from BMD and NASA-SSE department. Exploratory outcomes show that SRP can select six utmost salient features by providing 99.74% and 99.78% averaged testing accuracies for BMD and NASA-SSE data samples that are composed of 12 and 15 original features, respectively. Furthermore, the proposed model successfully obtained 0.26% and 0.22% MAPE for BMD and NASA-SSE data samples, respectively with a high correlation of about 99.97% within the actual and predicted data.

Key words — Artificial Neural Network, Ant Colony Optimization, Correlation Information, Feature Selection, Solar Radiation Prediction.

I. INTRODUCTION

Feature selection is one of the preliminary tasks for analyzing data such as information retrieval processing, pattern classification systems, and data mining applications. It reduces the number of features by removing noisy, irrelevant, and redundant data. [1]. This paper focuses on to select Solar Radiation features based on ACO and ANN.

Solar Radiation has been the most common origin of the heat energy in the earth that is necessary for different kinds of chemical and physical processes executed in the atmosphere, ocean, land, and other watery bodies. It is estimated that around 99.97% of the heat energy is obtained from solar radiation that is an essential part of a renewable energy source [2]. On the other hand, solar radiation is being considered as the most vital parameter in meteorology,

renewable energy, and solar energy conversion applications, especially for the sizing of standalone photovoltaic (PV) systems. In recent years, due to the inanition of fossil energy, the global climatic change is becoming more and more severe. Consequently, the applications of renewable energy sources are drawing more sights. Among the renewable energy sources, the most important application of solar energy has been the grid-connected PV plants and standalone PV systems, and that is increasing rapidly throughout the world in recent years [3].

It is known that solar radiation prediction has been the base for the prediction of power in PV generation. Therefore, it has been an increasing need for more precise and applicable modeling in case of the solar radiation prediction analysis [4]. Solar radiation data is one of the basic parameters of the solar energy research field that is not easily obtainable in most places due to the fierce cost and maintenance of the measuring instruments as well as non-availability of them at the meteorological stations [5]. That's why, Solar Radiation Prediction (SRP) for a specific location is an essential topic nowadays using several climatic variables.

A mentionable extent of research works has already been done in the literature sector related to the modeling and prediction of solar radiation for different solar energy applications [6], [7] that can be categorized widely into the three following ways: short-term prediction, daily prediction, and global prediction. The Short-term prediction is comprised of the detailed description of the current data up to 3–4 hours, while the prediction up to 7 days ahead in daily prediction. Global prediction normally refers to the prediction of the annual or monthly available resource. Among these prediction analyses, short-term solar radiation prediction services are very much important for PV grid operators with a view to ensuring the grid stability by which PV power plants that can be considered manageable.

Several models that already have been established in the literature sector for the prediction of the solar radiation that can broadly be classified into three general categories, such as, (i) Regression-based models, (ii) Statistical based models, and (iii) Artificial Neural Network (ANN) based models. In the regression-based models [8]–[12], solar radiation prediction uses an alternative measure instead of actually measured weather station data that is composed of the exploratory relevancies between solar radiation and the

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subsisting meteorological parameters. One of the most meaningful benefits in these approaches is, some meteorological parameters, such as ambient temperature and sunshine hours can easily be surveyed in most of the places. On the other hand, these approaches suffer from the nonlinearity behaviors of solar radiation that cannot be captured sufficiently. Hence, regression-based models do not provide the required accuracy for SRP [13].

Artificial Neural Network (ANN) is integrated with data processing, input variable selection and external optimization techniques to forecast the day ahead output power of a PV system. The forecasting model in [14] is able to outstandingly explain 97.68% of the total variation in the forecasted PV power. Moreover, the paper in [15] provides a compact guide of existing model modification and novel model development regarding predicting global solar radiation.

Prediction technique of solar radiation has also been accomplished using the Statistical based models (e.g., [16]-[22]), among which the persistence model is the easiest model [16] that pretends the future condition is exactly similar to the previous one. Another model is the regressive model that analyzes recent time-series behaviors to generate the forecasts [16]. Here, the regressive models can be normally partitioned into Autoregressive (AR) models and Moving Average (MA) models, or an alliance of these two in ARMA models or ARIMA models [16]. In [17], a simple ARMA model is used to predict the solar thermal systems in the cloudy areas of the UK, whereas the prediction of the daily solar irradiation at different cities of France and Peru has been done in [18]. A bi-linear time-series is used in ARMA model for predicting the daily solar irradiance in Kuwait [19]. Furthermore, in [20] and [21], ARIMA models have been used for solar irradiance prediction analysis of UK and Spain, respectively. One improvement of ARMA and ARIMA is the ARAMAX model introduced by [22] that allows the exogenous inputs to predict solar radiation. The ARAMAX model receives temperature, precipitation, insolation duration, and humidity as inputs that may easily be accessed from the local observatory.

The afore-mentioned works have already been published in the literature for modeling and predicting solar radiation in different solar energy applications. The analytic formula, numeric simulation or statistical approaches have been improved two or, three decades before to forecast solar radiation. These forecasting models, however, resulted in big errors. In order to surpass such restrictions, ANN-based models (e.g., [23]-[28]) have been introduced in recent years for SRP. Truly speaking, ANN has a robust optimizing ability for any kinds of continuous nonlinear function with providing a fair accuracy. Especially, ANN-based models can handle perfectly the noisy, incomplete, and non-linear datasets [29]. However, in [23], uses feed-forward ANN for predicting the global solar radiation for Nigeria involving the input parameters as sunshine duration, maximum ambient temperature and relative humidity that results in good relation between actual and predicted data. A model proposed in [24], collects the solar radiation data from 41 various stations in Saudi Arabia to find the radiation prediction accuracy using ANN. In this approach, the embodied input variables have been latitude, longitude, altitude, and sunshine duration. In [25] and [26], the solar radiation prediction for 12 different

cities in Turkey has been performed using ANN where the model uses training inputs of latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation. In respect of Bangladesh, until now a very few efforts have been done in the literature for performing the SRP. To solve such a problem, [27] presented a model that uses the input parameters like relative humidity, wind direction, wind speed, and precipitation for training the ANN. Another recent effort for Bangladesh in [28] that proposed a model in which performs into two ways: (a) finding the saliency of the input parameters, (b) measuring the SRP accuracy of the prominent feature subset using ANN.

The majority of the afore-mentioned SRP models, however, have attempted to find solutions for the SRP problems in either statistical or ANN-based utilizing the different types of meteorological input parameters. In this case, although such parameters are most significant to reach into the goal, some irrelevant parameters (or, features) might be available in the original input feature set. Following the concept of feature selection technique (FS) (e.g., [30]-[32], it can be said that the availability of irrelevant features may degrade the SRP accuracy. To overcome this limitation, FS concept is an interesting topic nowadays. It should be noted that, according to our knowledge, very few authors have given their concentration on feature selection in this area except [27]. That's why; most of the authors in the literature could not achieve optimal or near-optimal results in SRP problems, rather their solutions standing in the sub-optimal region.

Finding a subset of prominent inputs from the available features is called Feature Selection (FS) technique [31]. A detailed discussion about FS can also be found in [30]-[35]. However, several mentioned approaches for FS can widely be classified into the following 3 categories: Wrapper, Filter, and Hybrid [31], [32]. In a wrapper approach, a pre-composed learning model has been considered, where features are being selected based on the learning performance of that particular learning model [32], [33]. On the other hand, the statistical analysis of the feature set claims the filter approach without exploiting any learning model [36]. The hybrid approach utilizes the resultant capacity of the wrapper and filter approaches [33].

This paper proposes an effective solar radiation prediction model (SRPM) that exploits a hybridization of ACO search technique in the search space. The concept integrated into this model is proposed in [33]. However, the main focus of this model is to incorporate a hybrid search strategy to be intensified the global search of ACO in achieving the most salient features from the search space. The reason is that the hybrid search technique is more superior to the single search technique that makes the global search effective. Following such aspect, SRP tones the standard pheromone updating technique and heuristic information measurement systems in ACO depending on combining wrapper and filter approaches. Correlation information between the features and the output of ANN training have been employed in designing two rules for pheromone update technique and heuristic information measurement strategy. Although a variant of correlation information technique has also been used in other methods (e.g., [32], [37]) for solving classification problems on basis

of FS, neither correlation information technique nor ACO technique has been used before in the solution of SRP problem.

The latter part of this paper is being organized as follows. A detailed description of the proposed SRPM that has been narrated in Section II. Section III represents the results of the experimental studies, including the results of the proposed methodology and its effects on various considered techniques. Comparisons on results of SRPM with local and NASA-SSE data as well as with other methods have been showed in Section IV. Brief conclusions with few remarks have also been given in Section V.

II. PROPOSED SRPM

The proposed SRPM integrates correlation information technique among the features and the impact of ANN training's outcome to design the pheromone update rule and heuristic information measurement rule for the assistance of ACO global search. These two approaches resulting in SRPM increase the strength to achieve a quality solution for SRP from a recognized dataset. Fig. 1 illustrates a flowchart of the proposed SRPM model. The steps of SRPM model are narrated as follows:

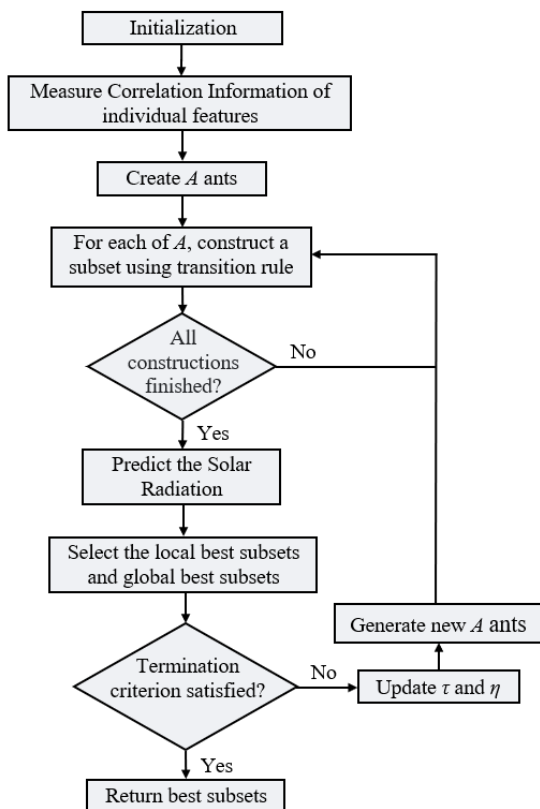


Fig. 1. Flowchart of the proposed SRPM.

Step #1: Let D be the provided data set where n is the number of independent features. Let the pheromone trails and the heuristic information to be initialized as τ and η , respectively for n features where τ and η are having equal values.

Step #2: Use n features individually to measure the correlation information using the correlation measurement method. Such correlation information of each feature is

considered here as the filter tool to design rules for selecting more distinct features. To find the features that are less correlated among the features of the data set, ants are guided here.

Step #3: Create a set of artificial A ants that is equal to n .

Step #4: Before the subset constructions (SC), decide the subset size, r for every A ants according to the range, i.e., $r \in [n_1, n_2]$, where n_1 and n_2 are the lower and higher number of features, respectively. Then, consider the existing probabilistic transition rule [35] to select features by which subsets can be constructed as follows:

$$P_i^A(t) = \begin{cases} \frac{[\tau_i(t)]^\alpha [\eta_i(t)]^\beta}{\sum_{u \in j^A} [\tau_u(t)]^\alpha [\eta_u(t)]^\beta} & \text{if } i \in j^A \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Here j^A is the possible feature set that is used for fulfilling the partial solution, τ_i and η_i are the pheromone and heuristic values related with feature i where $(i = 1, 2, \dots, n)$. On the other hand, the relative importance of the pheromone value and heuristic information are determined by α and β , respectively. Here, Eq. (1) shows the random behavior in SC primarily as the initial value of τ and η for all the individual features is equal.

Step #5: Check whether the subset constructions are completed or not. If the constructions are completed, then continue to the next step; otherwise, proceed back to the Step no 4.

Step #6: Follow the subset evaluation method to evaluate the subsets $S^A(t)$ and measure the Mean Absolute Percentage Error (MAPE), $M(S^A(t))$ of the prediction results of ANN. Here, $S^A(t)$ implies the subsets that are constructed by A ants at the iteration t .

Step #7: Choose the local best subset, $S^l(t)$ amongst all $S^A(t)$, and the global best subset, S^g amongst all $S^l(t)$ according to the best subset selection method mentioned in [30]. $S^l(t)$ is determined here in accordance with $\text{Min}(M(S^A(t)))$ and $t = (1, 2, 3, \dots, I)$; where I is the no of iterations.

Step #8: Check whether $S^l(t)$ can attain a predefined SRP performance, or the algorithm performance reaches an iteration threshold I_{th} and then terminate the FS process. Note that, I_{th} is nothing but a particular number of iterations in which the model cannot find any more changes within S^g . Else, continue the FS and store the performances of all local best subsets, $M(S^l(t))$ for further use.

Step #9: Follow the rules of pheromone update and heuristic information measurement to update the values of τ and η for all the features, respectively.

Step #10: Create a new set of artificial A ants and proceed further to continue the procedures similarly.

It is now clear that, the idea integrated behind SRPM is simpler, only selecting the salient features that are helpful for efficient ANN learning. A correlation information measurement method has been incorporated that doesn't require any high computational cost and can be carried out once throughout the whole FS process. For additional considerations, detailed aspects of SRPM have been provided in the latter part of this paper.

A. Subset Evaluation

In this context, an evaluation method for the subsets constructed by ants is discussed, where an ANN training module is considered. As a wrapper approach, the performance of ANN has been better than other filter approaches [32]. This work has been comprised of feed-forward ANN with fixed architecture. It means that the ANN is combined with 3 layers, which are a) input layer, b) hidden layer, and c) output layer. The size of the hidden layers has been kept fixed with a certain number of λ hidden neurons. The ANN module has been trained by the dataset of Solar Radiation using a Back Propagation (BP) algorithm [39]. Such an ANN module has not been an implicit discipline, instead of ANN, any other module, like SVM, could have been implemented for this evolutionary task. In this evaluation scheme, the ANN has been trained for a particular τ (a stable no of epochs), mindless of the algorithm itself, whether it has converged on a point or not. However, during the training of the ANN calculate the average training error that is considered here as mean squared error (MSE). Thus, the error, E_a , is calculated as:

$$E_a = \frac{1}{2p\tau} \sum_{p=1}^P \sum_{c=1}^C (t_c(p) - o_c(p))^2 \quad (2)$$

where $t_c(p)$ and $o_c(p)$ denote the actual and predicted responses of the c -th output neuron for the validation samples p , respectively. P and C symbols denote the no of total validation samples and output neurons, respectively. The performance of ANN in terms of prediction accuracy of the testing samples is measured by comparing the actual values and the ANN outputs during the same period of time. Furthermore, the Mean Absolute Percentage Error (MAPE) is one of the best relative accuracy measurements among the various prediction accuracy criteria [39]. However, MAPE is calculated here as:

$$MAPE = \frac{1}{N} \sum_{n=1}^N \left| \frac{P_n - \bar{P}_n}{P_n} \right| \times 100 \quad (3)$$

where, P_n and $\bar{P}_n$ represent the actual and predicted Solar Radiation and N is the total no. of samples available.

B. Hybrid Search Process

The Hybrid Search (HS) process, integrated into SRPM, consisted of the wrapper and the filter approaches. According to the concept, this technique is the first assumption in the FS-based SRP approaches. The authors proposed a hybrid search for the classification tasks in [33], where the information gain measurement technique is incorporated as a filter approach. It should be noted that information gain requires discrete target information to fulfill its measurement. As the SRP task consisted of the continuous-valued target information, the information gain technique is not suitable here to be used as the filter approach in designing the hybrid search process. Therefore, correlation information is considered here to select the more uncorrelated features from the constructed subsets. Finally, the ANN training outcome is incorporated in this hybrid search as a wrapper approach to be enhanced the

search capability. This HS technique has been comprised of two specific rules which are modified from [32], such as the pheromone update rule and heuristic information rule, which have been described later.

C. Pheromone Update Rule

Pheromone update in SRPM is the most vital aspect for selecting the salient features. Ants explore the features during SCs that are most suitable in the previous iterations. Such exploration is done using pheromone update rule consisted by local and global update. More specifically, those features that having significant role in the best feature subset in the current iteration only receive the global updates. It provides such features a large and equal quantity of pheromone update. The main aspect of the global update is to be inspired ants to select subsets with an effective MAPE. On the other hand, the local update not only makes irrelevant features to become less searchable, but also guides the ants for selecting the features that have not being selected before. A detailed discussion about this rule can be found in [33].

1) Random rule

The pheromone update rule for the random case of this paper presenting in (3) similar to the rule presented in [33]. At the initial iteration, the ants have been employed to build the feature subsets randomly, therefore, the pheromone update rule of all features i can be mentioned as follows:

$$\tau_i(t+1) = (1-\rho)\tau_i(t) + \frac{1}{f_i} \sum_{A=1}^n \Delta\tau_i^A(t) + e\Delta\tau_i^g(t)$$

$$\text{where, } \Delta\tau_i^A(t) = \begin{cases} M(S^A(t)) & \text{if } i \in S^A(t) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$\Delta\tau_i^g(t) = \begin{cases} M(S^I(t)) & \text{if } i \in S^I(t) \\ 0 & \text{otherwise} \end{cases}$$

In (4), i means the no. of feature ($i=1, 2 \dots n$), and f_i is the amount of the particular selected feature in the current iteration. $\Delta\tau_i^A(t)$ is the pheromone quantity taken in by the local update of feature i that has been included in $S^A(t)$ at iteration t . At the same time, the global update $\Delta\tau_i^g(t)$ is the pheromone quantity of feature i that has been included in $S^I(t)$. Finally, ρ and e directs to the terms of pheromone decay value and elitist parameter, respectively.

2) Probabilistic rule

A significant modification has been done here, which has been a variant from [33] presenting in (4). The modification is made in the second and third terms, which is the correlation term C_i as a replacement of information gain for each feature i .

$$\tau_i(t+1) = (1-\rho)\tau_i(t) + \sum_{A=1}^n \Delta\tau_i^A(t) + e\Delta\tau_i^g(t)$$

$$\text{where, } \Delta\tau_i^A(t) = \begin{cases} M(S^A(t)) \times C_i & \text{if } i \in S^A(t) \\ 0 & \text{otherwise} \end{cases}, \quad (5)$$

$$\Delta\tau_i^g(t) = \begin{cases} M(S^I(t)) \times C_i & \text{if } i \in S^I(t) \\ 0 & \text{otherwise} \end{cases}$$

Here, the third term of global update $\Delta\tau^t$ is assigned for feature i to be awarded, where $i \in S^l(t)$. The aim of this rule has been providing $\Delta\tau^t$ only to the significant features, because the global update has another important role in choosing the salient features.

D. Heuristic Information Measurement Rule

The measurement of heuristic information in ACO technique for the FS task is important in this point of view that a heuristic value, η , always expresses the attraction for each feature. The reason is that, without consideration of such measurement the search technique might be extremely greedy, and eventually effective outcome might not be found. Therefore, wrapper and filter approaches are considered to measure the heuristic information here. In this paper, the outcome of ANN, i.e., MAPE for each subset has been used as a wrapper tool. On the contrary, the value of correlation information for each feature has been considered as a filter tool. A detailed discussion about this rule can also be found in [33].

1) Random rule

This rule for the random case of this paper presenting in (5) similar to the rule presented in [30]. At the initial iteration, the ants have been brought into contact to build the subsets randomly, and the heuristic value of all features i can be estimated as follows:

$$\eta_i = \frac{1}{f_i} \sum_{A=1}^n M(S^A(t)) (1 + \phi e^{-\frac{|S^A(t)|}{n}}) \quad \text{if } i \in S^A(t) \quad (6)$$

2) Probabilistic rule

A significant modification is done here, which is different from the form mentioned in [31]. The actual modification is the correlation term C_i that is the replacement of information gain for each feature i . After completing the SCs of features depending on the probabilistic behavior, for estimating η of all the features i in the following iterations, the following rule is used as:

$$\eta_i = f_i \phi_i \sum_{A=1}^n M_a(S^k(t)) C_i (1 + \phi e^{-\frac{|S^k(t)|}{n}}) \quad \text{if } i \in S^k(t) \quad (7)$$

In these aforementioned rules, ϕ_i means the amount of a specific selected feature i from the previous iterations to current iteration, apart from the initial iteration. The multiplication of f_i and ϕ_i is done for providing a suitable exploitation ability for the ants during SCs. C_i denotes to the correlation information of feature i mentioned in [33]. The purpose of including correlation information C_i depends on the following two factors: (a) selecting the more obvious features during SCs, and (b) increasing the strength of the model. Thus, the best features receive an opportunity to get selection in the SC for different iterations that can enhance the prediction accuracy of the SRPM.

III. EXPERIMENTAL STUDIES

The performance of the proposed SRPM is evaluated over two sets of features for the same locations. One set of 12 well-renowned climatological features such as longitude, latitude, elevation, year, month, station constant, daylight hour, relative humidity, maximum temperature, minimum temperature, rainfall and wind speed, and the solar radiation data has been set as the output label. This dataset has been collected from the weather office of BMD. On the other hand, another 12 well renowned climatological features as longitude, latitude, elevation, year, month, day light hour, relative humidity, maximum temperature, minimum temperature, wind speed, clear-sky days, and daylight cloud amount and the solar radiation data has been set as the target being collected from NASA-SSE. These features have already been used in many of the solar radiation prediction models where ANN is applied in [23]-[28]. The experimental details, results, and Hybrid Search in FS have been described in the following sections. Eventually, to evaluate the performance of SRPM model, comparisons with other existing works mentioned in the literature are also presented.

A. Data Collections

In case of prediction of the solar radiation, data collection has been a crucial factor to strengthen the prediction capability of ANN. For this reason, SRPM has been trained over a huge amount of data for different locations. In detail, BMD has 35 stations to measure solar radiation and other climatological features, such as sunshine hour, maximum temperature, minimum temperature, humidity, wind speed, direction, and rainfall throughout Bangladesh. In this study, 14 years (i.e., 2000-2013) of monthly averaged data from the weather office of BMD for 35 stations have been used to train ANN. Furthermore, 22 years monthly averaged data were taken from NASA-SSE for the same geographical location of BMD stations for weighing the execution of the proposed model SRPM. It is necessary to get to know that real-world data is essential to train the ANN to be acquired knowledge through a learning process for a specific task. In this sense, a large dimensional data set is necessary for ANN training to gather the past knowledge that ultimately results in the prediction of the output variables.

B. Experimental Setup

For determining the effectiveness of SRPM for the solution of solar radiation prediction, extensive experiments have been performed. For accomplishing the FS and SRP task perfectly in SRPM, one simple step needs to be executed, which is identifying values for the user specified parameters. For the user-specified parameters, common parameters are listed in Table I. It should strongly be referred that parameters have not been marked specific to the algorithm used in this paper rather usual for any ACO-based FS algorithm using ANN. The afore-mentioned parameters had been selected after some initial runs. They were not supposed to be optimal. It is important to note that, the parameters denoted in Table I, among which suitable selection of the values of α and β , that is beneficial to achieve a significant capability of exploitation and exploration of ants for selecting the salient features [32].

TABLE I: COMMON PARAMETERS FOR ALL DATASETS

Parameters	Value
Pheromone Level (initial) for all features, τ	0.5
Heuristic value (initial) for all features, η	0.1
ε (used in subset size determination)	0.08 to 0.6
Pheromone Level strength, α	1
Heuristic value strength, β	3
Pheromone Decay parameter, ρ	0.4
Exponential Term control parameter, ϕ	0.1
Iteration threshold,	10 to 18
Learning Rate for BP	0.1 to 0.2
Momentum Term for BP	0.5 to 0.9
Weights (initial) of ANNs	-1.0 to 1.0
Number of Epochs for partial training, τ_p	20 to 40
Training Error threshold, λ	Depends on dataset
Training Threshold for Termination of ANN training, T	3

C. Experimental Results

The efficiency of SRPM model is determined by a set of experiments. For proving the robustness of the proposed model, 35 sub models have been developed for 35 different geographical locations using the data of BMD and NASA-SSE composed by 12 climatological features. The results of these sub models are then averaged to visualize the global robustness of the model SRPM shown in Table II. In Table II, solar radiation prediction results of the proposed SRPM for BMD and NASA-SSE data are shown for a single run. These results are made by the average of 35 SRPM sub-models for 35 different locations on the basis of the testing data samples formulated by the climatological parameters. Here, Table II shows the average testing results of PA, MAPE, RMSE, MSE and R for the individual 35 SRPM sub models in different 35 locations. The average percentage values of PA and MAPE are 99.49 and 0.49, respectively for BMD data. In case of NASA-SSE data, similar results can be seen that are 99.71 and 0.26, respectively. On the contrary, the better results of BMD and NASA-SSE data for the 3 stations among the 35 stations in case of average testing results of PA, MAPE, RMSE, MSE and R are shown in Table III. It is seen that performances of SRPM model are well and comparatively similar among these three stations. Particularly, the best performance for the BMD data is shown in the Dhaka region in respect of average testing PA and MAPE, which are 99.74 and 0.26, respectively, whereas Khulna region reflects the 99.78 and 0.10, respectively.

TABLE II: RESULTS OF SRPM FOR BMD AND NASA-SSE DATA FOR A SINGLE RUN

Data Sample	Avg. PA (%)	Avg. MAPE (%)	Avg. RMSE (%)	Avg. MSE (%)	Avg. R (%)
BMD	99.49	0.49	0.02894866	0.0846851	99.72
NASA-SSE	99.71	0.26	0.01966833	0.0494125	99.80

TABLE III: RESULTS OF SRPM FOR BMD AND NASA-SSE DATA FOR 3 STATIONS AMONG THE 35 STATIONS FOR A SINGLE RUN

Data Sample	Station Names	Avg. PA (%)	Avg. MAPE (%)	Avg. RMSE (%)	Avg. MSE (%)	Avg. R (%)
BMD	Chittagong	99.67	0.33	0.057628	0.003321	99.79
	Dhaka	99.74	0.26	0.045404	0.002062	99.84
	Khulna	99.66	0.34	0.059374	0.003525	99.30
NASA-SSE	Chittagong	99.76	0.24	0.041911	0.001757	99.79
	Dhaka	99.78	0.22	0.038419	0.001476	99.84
	Khulna	99.88	0.10	0.017463	0.000305	99.87

TABLE IV: PERFORMANCE OF SRPM MODEL AND THE RESULTS WERE AVERAGED OVER 15 INDEPENDENT RUNS

BMD data for Dhaka region for 15 independent runs				
Avg. PA (%)	Avg. MAPE (%)	Avg. RMSE (%)	Avg. MSE (%)	Avg. R (%)
99.70	0.30	0.052889	0.002745	99.82
NASA-SSE data for Khulna region for 15 independent runs				
99.75	0.25	0.043658	0.001906	99.91

As the models of Dhaka and Khulna region were found better among the 35 locations for BMD and NASA-SSE data, respectively, more experiments were conducted on the SRPM model for Dhaka and Khulna region. From this point of view, 15 independent runs on twelve climatological features; collected from BMD and NASA-SSE for SRPM model have been performed and the averaged results have shown in Table IV. It is found that the Averaged Percentage PA and MAPE for BMD testing data have resulted in 99.70 and 0.30, respectively, while 99.75 and 0.25 for NASA-SSE testing data, respectively. Furthermore, the values of averaged RMSE and MSE are lower for both data in testing cases of ANN that signifies that the training of ANN in testing data was performed well. On the contrary, the averaged percentage values of R among the selected salient features for both data cases are higher significantly, i.e., 99.82 and 99.91 for the Dhaka region and Khulna region, respectively. Thus, it can be said that the selected salient features performed by the proposed model having a stronger prediction capability.

Selection process of the salient feature subset has been presented in Fig. 2 (a, b). From this, it has been observed that when searching progresses the PAs have varied with the size of local best feature subsets. There have been various points in Fig. 2, where PAs have been recorded maximized, but the size of subsets remains different. It means that PA varies due to the variation of sizes of local best subsets in different iterations. In this case, the best solution is selected by figuring the deducted size of the subset.

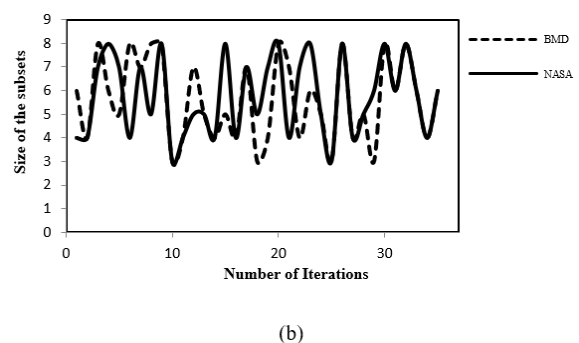
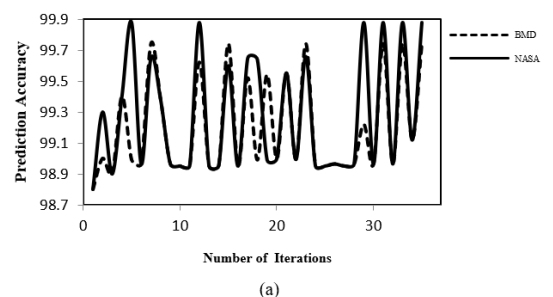


Fig. 2 (a, b). Finding best subset of the salient features for a single run.

With a view to observing the selection criterion of salient features in different iterations in SRPM, Fig. 3 exhibits the way of such indication for a single run. It has been seen that different features, such as, latitude, longitude, maximum temperature, minimum temperature, humidity, and daylight hour have been selected mostly by ants during SCs in comparison with the other features. For instance, feature longitude and latitude have the highest number of selections in all iterations for both BMD and NASA data, where the rest of features have the fluctuations in maximum selections. The selection criteria of features are usually carried out depending on the values of pheromone update (τ) and heuristic information (η) for individual features.

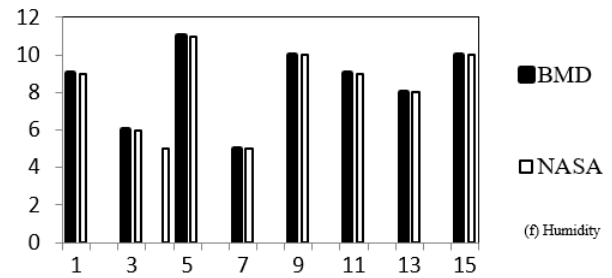
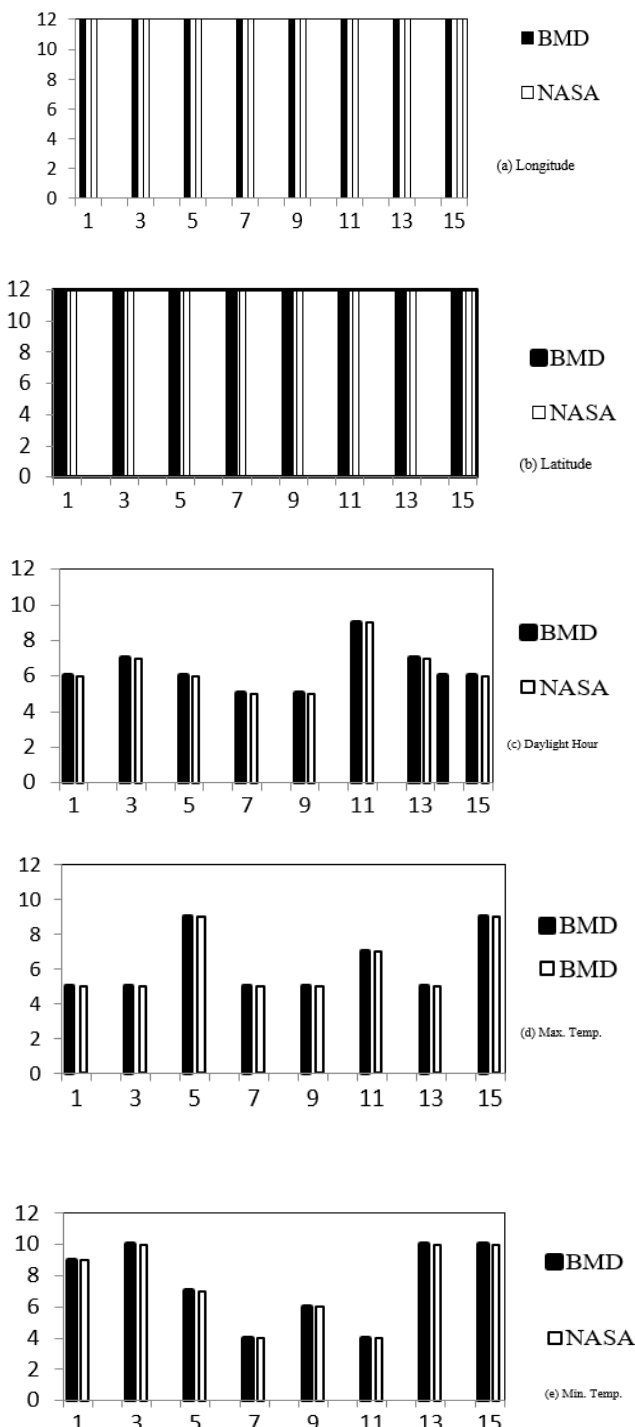
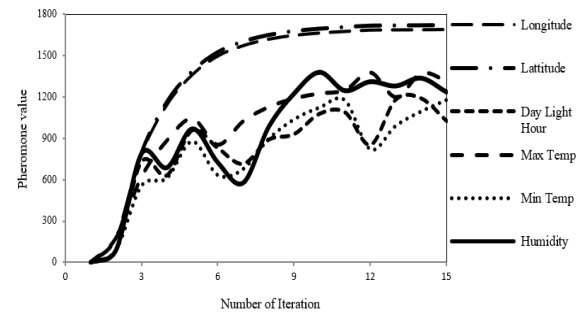
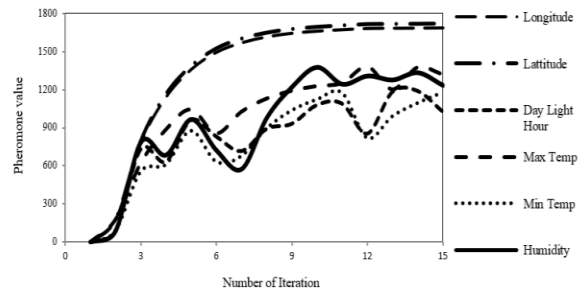


Fig. 3. Number of counts for the selections of salient features by different ants in different iterations for a single run.

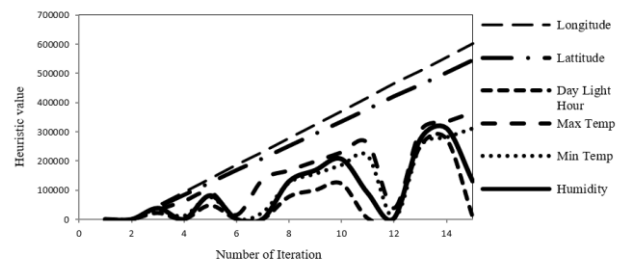


(a) BMD Data

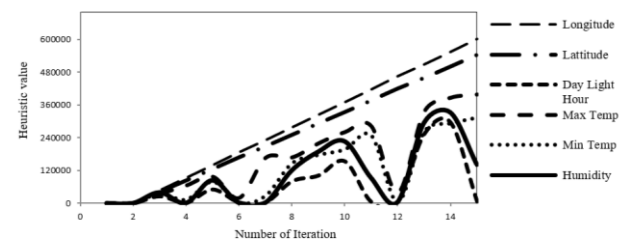


(b) NASA-SSE Data

Fig. 4. Distribution of Pheromone level of the selected salient features of (a) BMD data and (b) NASA-SSE data in different iterations for a single run.



(a) BMD Data



(b) NASA-SSE Data

Fig. 5. Distribution of Heuristic level of the selected salient features for (a) BMD data and (b) NASA-SSE data in different iterations for a single run.

For selecting the most salient features from the available feature set, the internal process of the proposed SRPM model can be seen in Fig. 4 and 5. As per ACO technique, those features having the most saliencies receive relatively the higher values of pheromone update level τ and heuristic level η [40]. According to this notion, Fig. 4 and Fig. 5 show that most salient features are 6 in number among the available 16 features. In the selected numbers, longitude and latitude have higher values of τ and η comparing to the others. On the other hand, the features Min Temp and Humidity have the lower values of τ and η as they are the least salient among the 6 selected salient features.

D. Effects of Subset Size Determination

Results showed in Table V prove the capability of SRPM for choosing the salient features. For example, SRPM selects 4.13 features on average from a set of 12 features in solving the solar radiation prediction for BMD data. But, in the case of NASA-SSE data, the results are most effective, since SRPM model select, on average, only 4.06 features from the set of 12 features. The positive outcome of selecting a tiny number of features (n_s) has been visualized when the PA values are being observed. For example, the average PA of selected features for BMD and NASA-SSE is about 99.74% and 99.78%, whereas the value is 95.5% and 97.5% with 12 features, respectively. Thus, it can be concluded that SRPM has owed a robust searching ability for giving high-quality solutions.

TABLE V: PERFORMANCE OF SRPM MODEL FOR FEATURE SELECTION AND RESULTS WERE AVERAGED OVER 15 INDEPENDENT RUNS

BMD Data							
Avg. result with all features				Avg. result with selected features			
n	SD	PA (%)	SD	n_s	SD	PA (%)	SD
12	0.00	95.5	1.12	4.13	0.82	99.74	0.40
NASA-SSE Data							
15	0.00	97.5	0.98	4.06	0.73	99.78	0.35

However, the effects which have been resulting from the bounded subset size for controlling the ants in a way as to build the subset in a deducted boundary that is not distinct. For observing such effects, a new set of experiments are performed. The setups for these experiments are likely to those which are narrated earlier. Only distinction between them is that SRPM did not consider bounded subset size before; on the other hand, the size of the subset for each ant had been decided randomly. Table VI shows the average results of the new experiments for climatological features over only 15 independent runs. The veritable effects of denoting the subset size during the FS process are obviously discernible. For example, the average values of n_s of SRPM without and with subset size determination are 7.11 and 4.13 for BMD, whereas 7.12 and 4.06 for NASA-SSE, respectively. In terms of PAs, Table VI also shows that the SRPM with subset size determination has resulted better than SRPM without subset size determination for the dataset. Moreover, the use of n_s has a quite little Standard Deviation (SD), as presented in Table VI. The small SDs implies the strength of the proposed model. Robustness or strength stands by the firmness of an algorithm under various initial conditions.

TABLE VI: EFFECT OF DETERMINING SUBSET SIZE ON THE AVERAGE PERFORMANCES OF SRPM

BMD Data							
FSSRP without bounded subset size				FSSRP			
n_s	SD	PA (%)	SD	n_s	SD	PA (%)	SD
7.11	1.37	98.67	1.10	4.13	0.82	99.74	0.40
NASA-SSE Data							
7.12	1.13	98.88	1.09	4.06	0.73	99.78	0.35

E. Effect of NN Structure and Number of Hidden Neuron

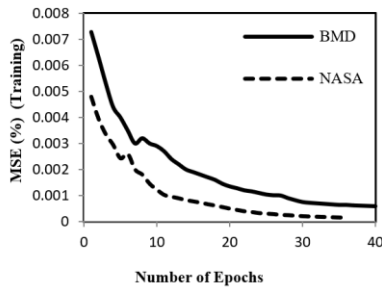
A successful evaluation function leads to finding high-quality solutions for SRPM in prediction. In this paper, the proposed model uses a constructive NN model that evaluates the subsets constructed by ants in each and every step during training. As training process progresses, the training error for the training set converges to a certain limit up to 40 and 35 epochs for BMD and NASA-SSE data, respectively (see Fig. 5(a). In Figs. 6(a,b), training is terminated at 40 and 35 epochs for BMD and NASA-SSE data, respectively, and where the number of hidden neurons selected is 3 for BMD data and 2 for NASA-SSE data, respectively, because at these instant validation error increases due to overtraining. Therefore, the training is stopped for a threshold value (i.e., %MSE), $V_{th} = 0.00205$, and $V_{th} = 0.00145$ for BMD and NASA-SSE data, respectively. These threshold values are determined by the trial and error basis. At the termination epoch, it is observed that, the prediction accuracy is 99.75% for BMD data and 99.79% for NASA-SSE on validation set shown in Fig. 6(c). The outcome of changing the number of hidden neurons of the proposed techniques into SRPM can be observed in Table VII for determining a robust ANN architecture. It is obvious that because of increasing the number of hidden neurons in ANN architecture up to 3 and 2 neurons for BMD and NASA-SSE data respectively, training, validation, and testing errors are decreasing due to the enhancement of network strength. The reason behind this is that the appropriate number of hidden neurons in an ANN provides a better generalization performance whereas the generalization performance of ANNs gets affected by the random selection of hidden neurons. Furthermore, the performance of any ANN is greatly reliable in its architecture [30]. This can be understood clearly in Fig. 7, where it is seen that a further increase in the number of hidden neurons produces oscillation. That's why the optimal number of hidden neurons in the hidden layer of ANN for BMD and NASA-SSE data is 3 and 2, respectively. This reduction in the number of hidden neurons also minimizes the computational cost for training and increases the strength of the ANN model.

TABLE VII: EFFECTS OF INCREASING THE NUMBERS OF HIDDEN NEURONS IN THE HIDDEN LAYER OF ANN

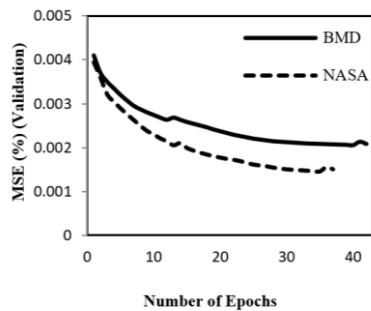
BMD Data			
No. of Hidden Neuron	MSE (%) (Training)	MSE (%) (Validation)	MSE (%) (Testing)
1	0.0070	0.0167	0.0169
2	0.0050	0.0127	0.0129
3	0.00059	0.00205	0.00206
4	0.0045	0.0130	0.0159
5	0.0020	0.0080	0.0090
6	0.0050	0.0132	0.0155
7	0.0030	0.0070	0.0085
8	0.0038	0.0135	0.0145

TABLE VII: CONT.

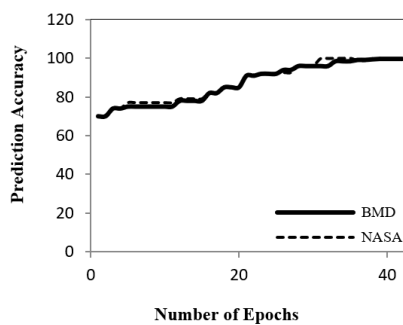
No. of Hidden Neuron	MSE (%) (Training)	MSE (%) (Validation)	MSE (%) (Testing)
NASA-SSE Data			
1	0.00305	0.00452	0.00454
2	0.00015	0.00145	0.00147
3	0.005034	0.0067	0.0068
4	0.0080	0.0080	0.0084
5	0.0054	0.0076	0.0078
6	0.00075	0.0055	0.0057
7	0.0065	0.0078	0.0079
8	0.00085	0.0058	0.0059



(a)

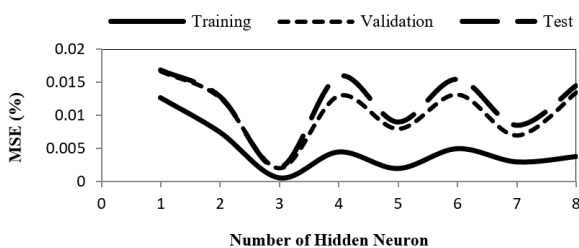


(b)

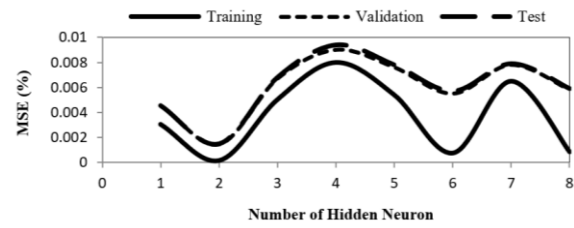


(c)

Fig. 6. Training process for weighing the subsets constructed by ants in the ionosphere dataset: (a) Training Error on Training set, (b) Training Error on Validation set, (c) Prediction Accuracy on Validation set.



(a) BMD Data

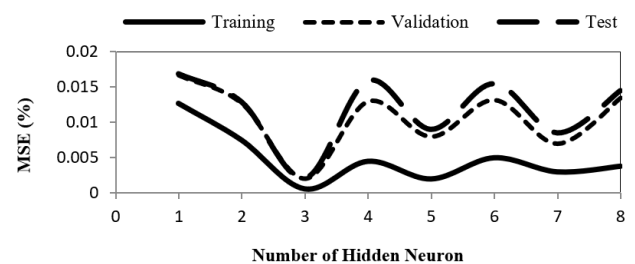


(b) NASA-SSE Data

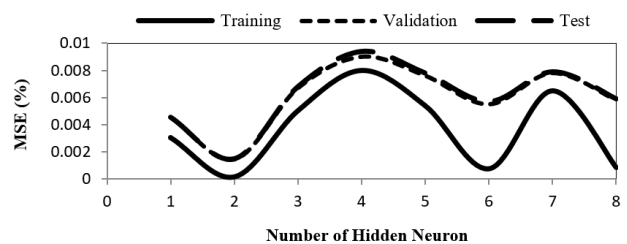
Fig. 7 (a, b). Error curves of Training set, Validation set and Testing set for BMD data and NASA-SSE data, respectively considering different number of hidden neurons in the hidden layer of ANN architecture.

F. Effect of Hybrid Search

The ability of SRPM for FS has been shown in Table V; however, the result of using Hybrid Search in SRPM for FS has not been cleared. Therefore, in this research, a new set of experiments has been introduced to observe those results. The only difference is that in this case, SRPM has ignored the modified rules of pheromone update and heuristic value for each feature. Replacing that, standardized rules were executed. With these considerations, the incorporation of the correlation information has been avoided and the concept of random and probabilistic behaviors during SC for both specific rules has also been carried out. Moreover, the exponential terminology in the heuristic measurement rule has been totally ignored. The averaged outcomes of the new experiments for the BMD and NASA-SSE datasets have been shown in Table VIII for over 15 independent runs. Certain results of using a hybrid search in SRPM are clearly discernible here. For example, for all climatological features of BMD and NASA-SSE datasets, the average PAs of SRPM for with and without hybrid search was 99.74%, 99.78%, and 95.2%, 96.5% respectively. On the contrary, in order to select features for BMD and NASA-SSE datasets, the average values of n_s of SRPM with and without hybrid search were 4.13, 4.06, and 6.14, 6.05, respectively.



(a) BMD Data



(b) NASA-SSE Data

Fig. 7 (a, b). Error curves of Training set, Validation set and Testing set for BMD data and NASA-SSE data, respectively considering different number of hidden neurons in the hidden layer of ANN architecture.

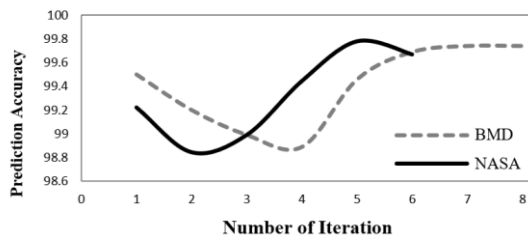
TABLE VIII: EFFECTS OF APPROACHING HYBRID SEARCH ON AVERAGE PERFORMANCES OF SRPM. RESULTS WERE AVERAGED OVER 15 INDEPENDENT RUNS

BMD Data							
Result without hybrid search				Result with hybrid search			
n_s	SD	PA (%)	SD	n_s	SD	PA (%)	SD
6.14	1.45	95.2	1.51	4.13	0.82	99.74	0.34
NASA-Data							
6.05	1.32	96.5	0.98	4.06	0.73	99.78	0.27

With a view to visualizing how hybrid search acts a vital role in SRPM for FS tasks, a set of experiments was performed under the same initial conditions. Figs. 8 (a,b) show the PAs of SRPM without and with hybrid search, respectively. These PAs were generated by local best subsets in different iterations of a single run. These figures show the positive nature of implementing hybrid local search in SRPM.



(a) without considering the hybrid search



(b) with considering the hybrid search

Fig. 8. Prediction Accuracies (PAs) for the dataset (a) without considering the hybrid search and (b) with considering the hybrid search.

From Fig. 10 it can be seen that a better PA has been gained barely in the time of initial iteration for the exquisite survey by the ants while finding the salient features. For the next iterations, the PAs have agitated up to a higher iteration, 20, however, have not been capable to reach the best position. This situation came up because of the inexistence of hybrid search, which has affected in a poor search in SRPM. The inverse continuity can also be seen in Fig. 9(a), where the search was sufficiently robust that a very low number of iterations, by which SRPM has been capable to again the best accuracy 99.74% and 99.78% for BMD and NASA-SSE data, respectively of the salient feature subset. After that, SRPM has terminated the searching for salient features. The reason behind such high performance of FS has been the execution of the hybrid search.

G. Correlation Information

In this context, the aim of measuring correlation information of the selected salient features is how much they are correlated among themselves and different from each

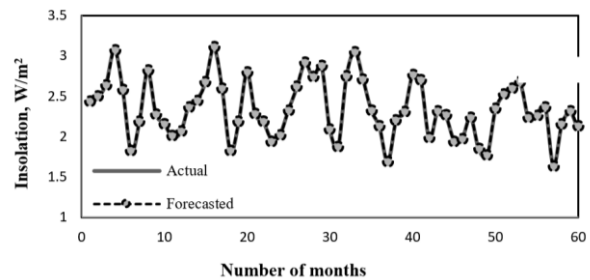
other. Table IX shows that the selected features are mostly uncorrelated among the data set. It also implies the more distinct selected features that consequence the robust learning of ANN. Finally, the incorporated technique correlation information in the searching process of the proposed model enables in selecting the distinct features that resulting in the enhancement of solar radiation prediction ability of the proposed SRPM.

TABLE IX: CORRELATION INFORMATION (CI) OF SELECTED SALIENT FEATURES

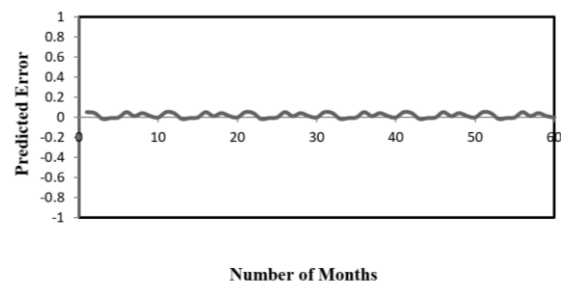
BMD Data						
Features	Longitude	Latitude	Day Light	Relative Humidity	Max T	Min T
Correlation	4.81	5.91	5.83	5.55	25.96	32.85
Less	95.19	95.086	90.17	94.45	74.04	67.15
Correlated						
NASA-SSE Data						
Correlation	4.81	5.91	5.83	7.55	10.96	8.96
Less	95.29	95.10	91.05	93.56	94.10	91.23
Correlated						

H. Predicted Results

For observing the prediction results of our proposed model SRPM, a sample analysis of the Dhaka region has been considered among the others. Fig. 9(b) shows the prediction and error curves, respectively for the Dhaka region. It is found that actual curve and forecasted curve have overlapped each other, where the error is found minimum.



(a)



(b)

Fig. 9 (a, b). Predicted curve and error curve for Dhaka region.

IV. COMPARISONS

This article has been comprised of the results of SRPM which have been obtained on two datasets, such as, local investigated data and NASA-SSE data for Bangladesh were compared. Furthermore, the results of SRPM on local investigated data of Bangladesh were compared with the results of the climatological data of Pakistan and India. Here, all the results were formulated on average for different locations of Bangladesh. To present the perfect comparisons

of SRPM, 35 ANN models for 35 stations were considered. Furthermore, for more precise comparisons, the results are compared with other solar radiation prediction models proposed in the literature to show the efficiency of SRPM model in prediction. For comparison purposes, three performance parameters, such as PA, MAPE, and R are used.

A. Comparison with Local and NASA-SSE Data

The results of SRPM obtained on local investigated data and NASA-SSE data for Bangladesh were compared Table X in terms of MAPE, PA, and R for the datasets of 35 locations for Bangladesh. The results were averaged over these locations of Bangladesh. It is observed in Table X that, the averaged PA in the testing phase is 99.71% for NASA-SSE data and 99.49% for local data with MAPE 0.26% and 0.49%, respectively for 35 stations. On the other hand, Table XI also indicates the variation of MAPE is 0.07-0.31% for NASA data and 0.14-0.66% for local data for different locations. In the case of feature selection, Table XII shows the PA that is 99.78% for NASA-SSE data with minimum SD.

TABLE X: COMPARISONS BETWEEN LOCAL AND NASA DATA. THE RESULTS WERE AVERAGED OVER 35 LOCATIONS IN BANGLADESH

Local Investigated Data				NASA-SSE Data		
Cases	PA (%)	MAPE (%)	R (%)	PA (%)	MAPE (%)	R (%)
Training	99.60	0.42	99.81	99.87	0.14	99.83
Testing	99.49	0.49	99.72	99.71	0.26	99.80

TABLE XI: COMPARISONS BETWEEN LOCAL AND NASA-SSE DATA FOR VARIOUS LOCATIONS IN BANGLADESH

Local Investigated Data				NASA-SSE Data			
Location	Cases	PA (%)	MAPE (%)	R (%)	PA (%)	MAPE (%)	R (%)
Dhaka	Train	99.86	0.14	99.93	99.93	0.07	99.97
	Test	99.74	0.26	99.84	99.78	0.22	99.84
Barisal	Train	99.75	0.25	99.86	99.89	0.2	99.92
	Test	99.5	0.5	99.83	99.74	0.3	99.84
Khulna	Train	99.76	0.24	99.54	99.93	0.08	99.97
	Test	99.66	0.33	99.30	99.88	0.1	99.87
Rajshahi	Train	99.59	0.41	99.09	99.79	0.21	99.15
	Test	99.34	0.66	98.84	99.69	0.31	98.86

TABLE XIII: COMPARISONS BETWEEN RPT MODELS

Existing Models	Used AI tools	Prediction to the Country	MSE (%)	RMSE (%)	PA (%)	MAPE (%)	R (%)
Proposed RPT	ACO based Model	Bangladesh	0.00014	0.012	99.93	0.07	99.9
Dozen et al. ²⁴	ANN model	Turkey	-	-	-	5.28	-
Quaiyum & Rahman ²⁶	ANN Model	Bangladesh	0.29	-	-	-	-
Rahman & Mohandes ⁴⁰	ANN model	Saudi Arabia (Abha City)	-	-	-	4.49	-
Will et al. ⁴¹	Genetic Algorithm	North Argentina	-	-	-	-	92.8
Khan et al. ⁴²	ANN Model	Bangladesh	-	-	-	-	97.4
Yadav & Chandel ⁴³	ANN Model	India	0.0024	-	-	0.27	-
Alam et al. ⁴⁴	ANN Model	India	-	4.5	-	-	-
Benghanem et al. ⁴⁵	ANN model	Al Madinah (Saudi Arabia)	-	-	-	-	97.6
Azadeh et al. ⁴⁶	ANN model	Iran	-	-	94	3	-
Iqdour & Zeroual ⁴⁷	Takagi-Sugeno (TS) Fuzzy System	Marrakesh (Morocco)	-	7.6	-	-	-
Şen et al. ⁴⁸	Fuzzy model and Genetic algorithm (Geno -Fuzzy)	Turkey (Istanbul)	-	0.04-0.05	-	-	-
Hasni et al. ⁴⁹	ANN model	Algeria	-	-	-	2.99	-

TABLE XII: COMPARISONS BETWEEN LOCAL AND NASA DATA AFTER FEATURE SELECTION. THE RESULTS WERE AVERAGED OVER 35 LOCATIONS IN BANGLADESH

Local Data				NASA data			
Avg. Result with selected features				Avg. Result with selected features			
n _s	SD	PA (%)	SD	n _s	SD	PA (%)	SD
6.13	0.82	99.74	0.40	6.06	0.73	99.78	0.35

B. Comparison with Other Works

In this research, the results of the mentioned SRPM have been assimilated with the other existing models shown in Table XIII. It should be noted that the technical background of the proposed SRPM is quite different from those discussed in [27], [41]-[50]. In these models, solar radiation prediction was done using the different features that had been found on the basis of knowledge or, availability where no attempt was found to be searched the best feature subset. Furthermore, MATLAB nftool was used in [27] and [43] to design the prediction model without selecting the best climatological features in case of Bangladesh. In [44], the prediction model used the MATLAB nftool with the features of latitude, longitude, height above the sea level, and sunshine hour. Genetic algorithm had been used in [42], where the measurement of correlation information between actual and forecasted data was integrated. On the contrary, the fuzzy systems as well as the combination of genetic algorithm and fuzzy system were introduced in [48].

From Table XIII, it has been seen that the mentioned SRPM model shows the maximum PA (99.93%) and minimum MAPE (0.07) comparing to the other existing models. The reason is that the proposed model has been integrated by an efficient ANN structure that utilizes the FS technique using ACO and correlation information. It should be noted that the other models utilize the different data of different countries, where our model uses the data of Bangladesh. That's why, these comparisons may not be perfect.

V. CONCLUSION

In this paper, an effective model (i.e., SRPM) has been developed for forecasting solar radiation using ACO and ANN. In SRPM, most prominent climatological features have been picked for improving the prediction accuracy. To determine the mobility of SRPM, two sets of new rules are implemented for pheromone updating and for measuring heuristic value, where correlating information and the outputs of ANN have been put in. It has been shown through various experiments that SRPM has performed well in collecting 12 solar radiation data samples from BMD, where it has selected six most prominent features effortlessly with efficient Prediction Accuracy. These selected features are longitude, latitude, daylight hour, maximum temperature, minimum temperature, and humidity. Moreover, the averaged Prediction Accuracy (PA) of SRPM for 35 stations of BMD in the testing state is 99.74% comprising of the MAPE of 0.26% (see Table II). The developed SRPM also presents a high correlation of 99.93% (see Table 3) in between the actual and predicted data. On the contrary, the results of gaining the low standard deviations for the prediction accuracies represents the strength of this model. A comparative analysis of results presented in Table XIII effortlessly shows that SRPM can outperform the other existing models exceedingly well. So, it can be concluded that the developed SRPM model has the ability to choose the prominent features and to forecast the solar radiation at any location in the world if the necessary relevant data from the locations are provided accurately.

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