Machine learning prediction approach for dynamic performance modeling of an enhanced solar still desalination system

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Abstract

An enhanced design for a solar still desalination system which has been proposed in the previously conducted study of the research team is considered here, and the experimental data obtained during a year are employed to develop ANN models for that. Different types of artificial neural network (ANN), as one of the most popular machine learning approaches, are developed and compared together to find the best of them to predict the hourly produced distillate and water temperature in the basin, which are two key performance criteria of the system. Feedforward (FF), backpropagation (BP), and radial basis function (RBF) types of ANN are examined. According to the results, by having the coefficients of determination of 0.963111 and 0.977057, FF and RBF types are the best ANN structures for estimation of the hourly water production and water temperature in the basin, respectively. In addition, the annual error analysis done for the data not used to develop ANN models demonstrates that the average error in prediction of the hourly distillate production and water temperature in the basin varies from 9.03 and 5.13% in January (the highest values) to 4.06 and 2.07% in July (the lowest values), respectively. Moreover, the error for prediction of the daily water production is in the range of 2.41 to 5.84% in the year.

Keywords Artificial intelligence · Backpropagation artificial neural network · Experiments · Feedforward artificial neural network · Radial basis function artificial neural network

Introduction

The environment is a vital resource that needs to be protected and conserved [1–4]. To offset the negative impact of anthropogenic activities associated with the extraction and burning of fossil fuels, alternative energy sources need to be exploited [5–10]. Solar energy is one of the cleanest and cheapest sources of energy [11–15]. Solar energy is much more predictable than its rival, i.e., wind energy [16–18]. It is widely available in most areas of the world [19–21]. Solar still as a type of solar technology is widely used for producing freshwater from saline water [22–24]. Such a system, due to its high reliability as well as usability, has attracted increasing attention in recent years [25–27]. In a solar still system, impure water in the basin is evaporated by the heat of the sun [28–30]. Then, evaporated water is cooled and collected in the water collection through [31–33]. Therefore, pure water is obtained from a brackish one.

Thermal analysis is an important part for modeling a system [34–37]. Therefore, many studies have focused on modeling the different types of solar stills thermally to analyze the performance of these systems. Hence, the need for modeling the solar still has intensified over the past several years, leading to the development of various thermal models. Data-driven methods as a means to improve the runtime of numerical modeling and design optimization with reliable accuracy are drawing attention towards themselves in this way. Machine learning (ML) has proven its capability in engineering simulations among data-driven approaches

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due to being more accessible and easier to handle. Also, among ML algorithms, artificial neural networks (ANN) have a widespread acceptance in many applications such as diagnostic prediction, e.g., knock occurrence in internal combustion engines [38] and membrane degradation in fuel cells [39], and performance prediction, e.g., heating pumps [40], photovoltaic solar modules [41], and evaporative coolers [42], dehumidifiers [43], and so on. Besides, contrary to linear regression algorithms, ANN can extract the nonlinearity relationship between the input–output data.

Table 1 presents a list of the recently done investigations in the field of modeling the performance of a solar still using ML. In this table, a brief summary of each work is provided while a question about application of different types of ANN for modeling and comparing them is asked.

As answering the question in Table 1 reveals, although different conditions for adjusting parameters like number of layers and hidden neurons in each layer, as well the learning algorithm has been examined, in no study in the past, different types of ANN have been developed and compared together. Therefore, based on the identified gap, the current study is done, in which feedforward (FF), backpropagation (BP), and radial basis function (RBF) types of ANN are developed to estimate the values of the hourly distillate and water temperature in the basin, as two main characteristics of a solar still. The experimental data recorded by the research team are used as the input data for modeling. The models are developed, and then, by employing an error analysis, the best of them is found for each case. In addition, the ability of the best found type of ANN for each case to estimate the values not employed for model development is evaluated for different hours of a sample day, while the profiles for average error values in various months of a year are also discussed in detail.

The investigated solar still and experiments

As indicated, in this study, an enhanced design for the solar still system, which was originally introduced by Sohani et al. [1], is investigated, and the experimental data for that are employed as the input data for obtaining different types of ANN model.

The experiments are conducted on the test rig located at 51.4 degrees E, 35.7 degrees N in Tehran, Iran [54]. Figure 1 schematically represents the experimental test rig, containing a solar still unit placed on the wheels by rods with varying lengths. The rods' variable length can change

Table 1 A quick introduction of the related recent works done in the topic of this investigation

Study	Year	A brief description	Were different types of ANN considered and compared together?
Abujazar et al. [44]	2018	A feedforward type of ANN was developed to determine the values of pure water production of a solar still system	No
Wang et al. [45]	2019	A tubular type of solar still was considered, and the simulation of that was done by ML. The water production rate of the solar still was taken into account as the modeled parameter	No
Mashaly et al. [46]	2019	Different kinds of ML including one ANN structure were examined and evaluated for modeling the performance of a solar still. The system was an almost simple passive design	No
Sharshir et al. [47]	2019	A pyramid solar still was considered, and the distillate production and energy efficiency indicator at each hour were predicted by means of ML	No
Chauhan et al. [48]	2019	The amount of water production in a solar still was considered as an output, and it was predicted by ANN	No
Bahiraei et al. [49]	2020	A novel design for a solar still which worked based on nanofluid concept and in which thermoelectric units were used, was proposed, and then, ANN was utilized to estimate the performance	No
Nazari et al. [50]	2020	ANN was employed, and a number of technical performance parameters of a solar still including water production and efficiency values were modeled	No
Chauhan et al. [51]	2020	By the aid of ANN, the thermophysical characteristics of the wet air in the solar still were determined	No
Essa et al. [52]	2020	Harris Hawks optimizer in combination with ANN was utilized to provide a model for estimation of water production of a solar still	No
Elsheikh et al. [53]	2021	A stepped type of solar still was investigated, and the performance of that was simulated using ANN. The distillate production was the output of modeling, and the results of operation of the proposed design were compared with a conventional technology for solar stills	No

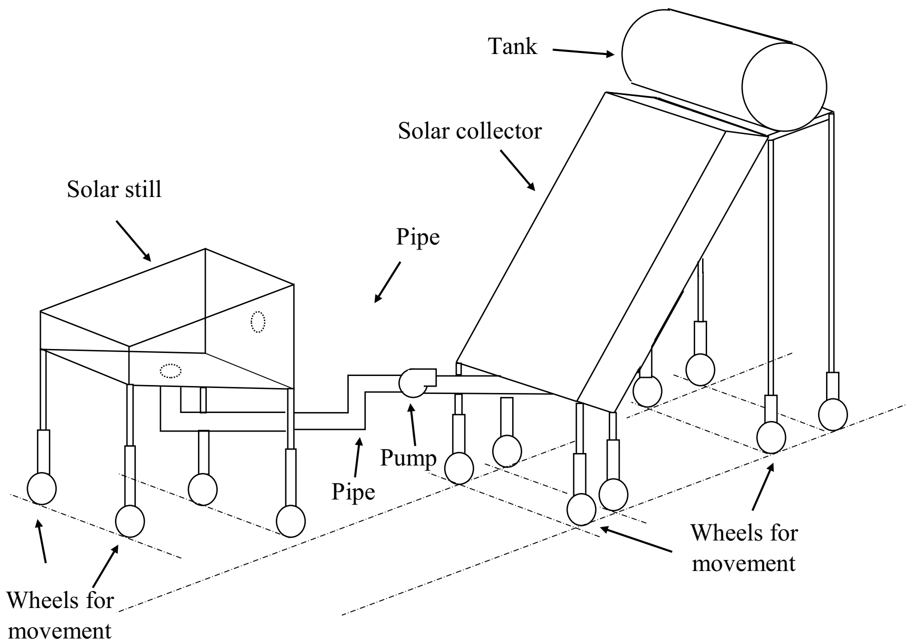

Fig. 1 Schematic of the enhanced design for solar still desalination system which is investigated in this study [1]

the distance between the collector and wheels and, eventually, the slope. As can be seen, the solar still unit consists of a feed-water tank, a solar still, and a 3 m^2 flat-plate solar collector, of which two last items are linked together through plumbing. A pump is also taken into account to sustain the energy enough in the network grid during the experiments. In addition to the water tank above the solar collector, two reservoirs to accumulate salty water and freshwater are accommodated close to the solar still, not shown in Fig. 1.

The solar still with an area of 1.4 m^2 comprises a basin, glass, polycarbonate box, isolation cover, and the half-pipe to collect freshwater. The bottom side of the tested solar still is painted in the color of black to maximize the absorption of solar radiation. The flat-plate solar collector insulated with glass wool and the steel pipe are chosen to provide a long-term life during the test period while maintaining a high heat transfer rate.

The experiments were carried out during a year. They start from 8 in the morning and continue up to 16 in fall and winter (October to March), and up to 18 in the spring and summer (April to September). Other details including the time resolution and the employed measurement devices are completely similar to the previous recent investigation of the research group, i.e., reference [1], and found there.

Artificial neural network

Modeling means finding a means to obtain the value of an output based on the effective input parameters [55–57], and artificial neural network (ANN) is one of the robust techniques for this purpose [58–60]. ANN is made by the connection of a number of computational units, which are called neurons. Every neuron is composed of a net and a transform function. The input goes and is multiplied by a mass. Then, the outcome is fed into the transform function, and the output is introduced as the final given value.

In order to build neural networks in this work, the developed codes in MATLAB software program are employed. The developed codes are the ones which have been previously used in the past investigations of the authors to simulate the performance of other energy systems using ANN, such as [41, 42], and [43]. The codes work based on the flow chart presented in Fig. 2.

In this study, the following items are considered as the effective input parameters of ANN:

- Ambient temperature,
- Wind speed,
- The radiation received from the sun,
- Depth of water in the basin,

Outputs are also:

- Water temperature in the basin,
- Distillate production,

which are the two key performance criteria of the system. In addition,

- Coefficient of determination (R^2)
- Mean absolute error (MAE)

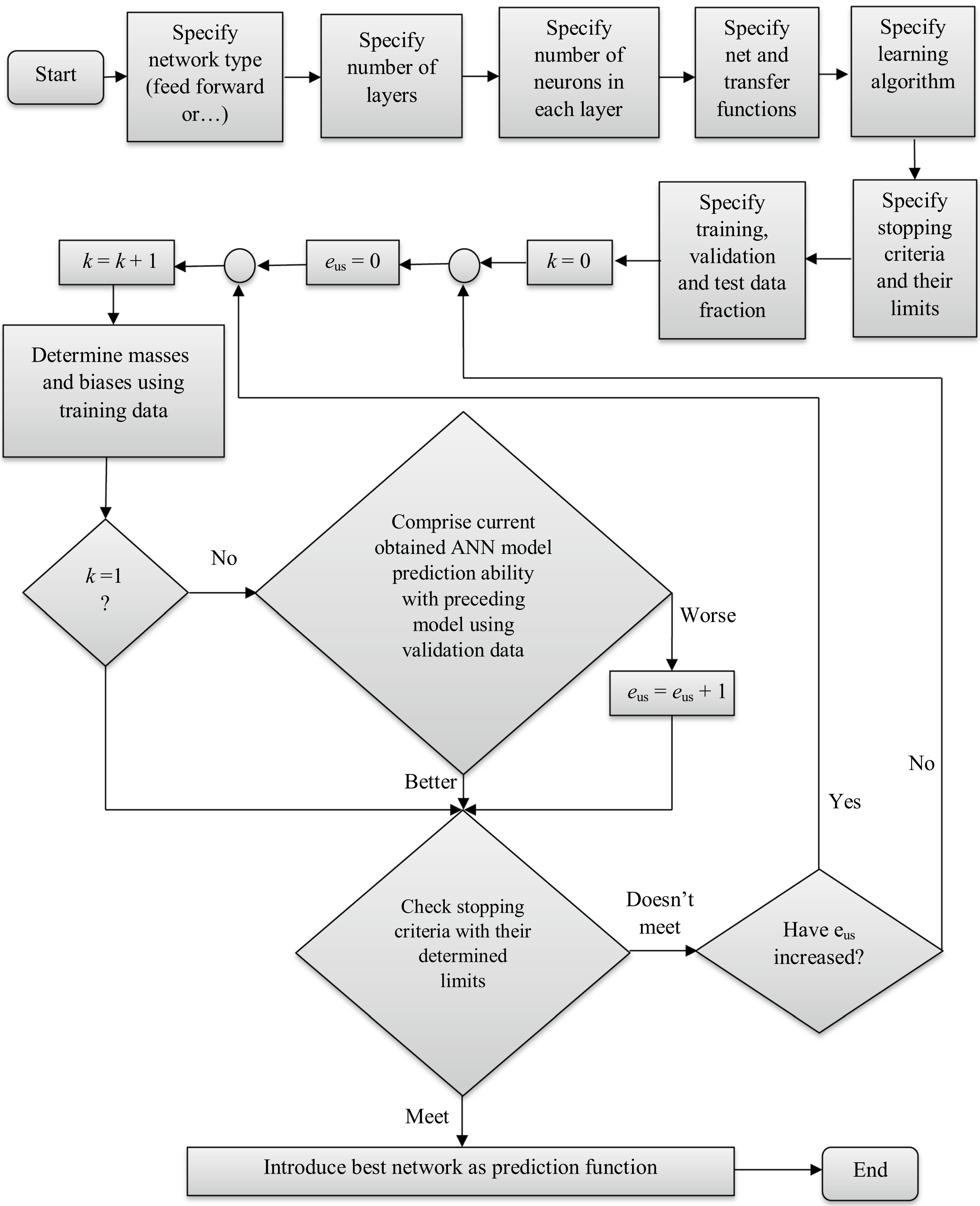

Fig. 2 Process of finding an ANN for prediction of an output based on the effective input parameters [43]

are considered as the error-related parameters by which the prediction ability of different types of ANN is evaluated.

More details, including the working principles and differences of the three considered types of ANN, in addition to the definition of R^2 and MAE have been described in several works in the literature like [61–64]. For this reason, here for not making the research item lengthy with repetitive explanations, only a general description is provided while the references are suggested to find more information.

Results and discussion

Results of this study are presented and discussed here. For this purpose, initially, uncertainty evaluation for the conducted experiments is done in the first part of this section. After that, error analysis is carried out in the second part of this section to find the best ANN structure for distillate production and water temperature in the basin, and next, the prediction accuracy of the best found ANN types to estimate the values of the two mentioned criteria in addition to the cumulative water productivity is evaluated in the third part of this section for a sample day, and in the fourth part of this section during a year.

Uncertainty evaluation for the conducted experiments

For the parameters measured during the experiments, the relative uncertainty values are computed, which are listed in Table 2. Table 2 indicates that the average uncertainty values for radiation received from the sun, ambient temperature, water temperature in the basin, distillate produced by the solar still, and wind speed are 0.037, 0.932, 0.336, 1.305, and 0.048%, respectively. Those values are close to other experimental studies in the literature, including Dumka et al. [65] and Kabeel and Abdelgaied [66], which suggests that the done experiments have enough accuracy and could be utilized for developing different ANN models.

Table 2 Evaluation of the accuracy of the experiments using average relative uncertainty values

Measured parameter	Average relative uncertainty value/%
Radiation received from sun	0.037
Ambient temperature	0.932
Water temperature in the basin	0.336
Distillate produced by solar still	1.305
Wind speed	0.048

Error analysis for different developed ANN models

Having got assured from the accuracy of the conducted experiments, developing ANN models with the three mentioned structures is carried out using MATLAB software program, and models to predict water temperature in the basin and produced distillate are found. Following similar fashion as the previously done studies by authors, including [42, 43], and [41], for each structure, a variety of adjusting parameters, including the number of neurons in different layers, training algorithms, the share of training, validation, and test data, and so on, are examined, and the best one for the water temperature in the basin and the produced distillate is found for each structure. After that, the best model for each of the two mentioned parameters is determined using mean absolute error (MAE) and coefficient of determination (R^2), as the two widely used error-related criteria for evaluating ANN models.

The results are reported in Table 3 for the water temperature in the basin and in Table 4 for the produced distillate. As seen, with MAE and R^2 of 3.56% and 0.963111, FF type of ANN is chosen as the best prediction way for the water temperature in the basin among the available items, whereas

Table 3 Values of the mean absolute error (MAE) and coefficient of determination (R^2) for the three different ANN types developed in this study for prediction of water temperature in the basin

ANN type	Mean absolute error/%	Coefficient of determination (R^2)
BP	5.91	0.942567
FF	**3.56**	**0.963111**
RBF	4.47	0.956798

For each type, the value for best of that is reported. The bold row shows the best ANN type

Table 4 Values of the mean absolute error (MAE) and coefficient of determination (R^2) for the three different ANN types developed in this study for prediction of the produced distillate

ANN type	Mean absolute error/%	Coefficient of determination (R^2)
BP	5.25	0.934615
FF	5.17	0.934889
RBF	**2.82**	**0.977057**

For each type, the value for best of that is reported. The bold row shows the best ANN type the foremost ANN for the produced distillate is RBF. RBF is able to estimate the produced freshwater by MAE of 2.82% and R^2 of 0.977057.

Hourly performance of the best found ANN models

It has been revealed that FF ANN and RBF ANN offer the highest accuracy for estimation of water temperature in the basin and produced distillate, respectively. Considering this point, in this part, the hourly performance of the best found ANN models for the prediction of the two mentioned criteria is investigated here. The data recorded on September 9, 2019, which have not been utilized as the input data of the created ANN models, and they could be also found in [1], are used for this goal.

Figure 3 illustrates the values for hourly produced distillate. Based on this figure, the error in prediction of the freshwater production by the system goes down by getting close to the hour with the peak temperature and irradiance levels, i.e., 13. For instance, at 9, the best ANN model gives the value of 259.3 mL for the produced distillate, while the experimental measurements reveal the actual water production is 5.69% more, i.e., 274.9 mL. Nonetheless, the error reaches to almost a half, i.e., 2.49% at 13. At 13, the predicted and measured values are 1305.8 and 1339.2 mL, respectively. The absolute error increases again in the afternoon where it has the values of 4.72, 5.33, and 11.91% at 16, 17, and 18, respectively.

The general variation trend of error for the water temperature in the basin is quite similar to the produced distillate as Fig. 4 demonstrates. Nonetheless, in this case, in contrast to water production, the error at the beginning and the end of the day is not very higher than the middle of that. At 8, 13, and 18, the absolute error values for prediction are 3.96, 2.50, and 3.06%, whereas the corresponding values for the freshwater production are 16.30, 2.49, and 11.91%, respectively.

Moreover, the error for all the hours is lower than 4.5%, which indicates that the provided model has a high accuracy level for all hours of the day. Such error level for prediction is very acceptable since it leads to only almost 2 °C difference between the actual and estimated values.

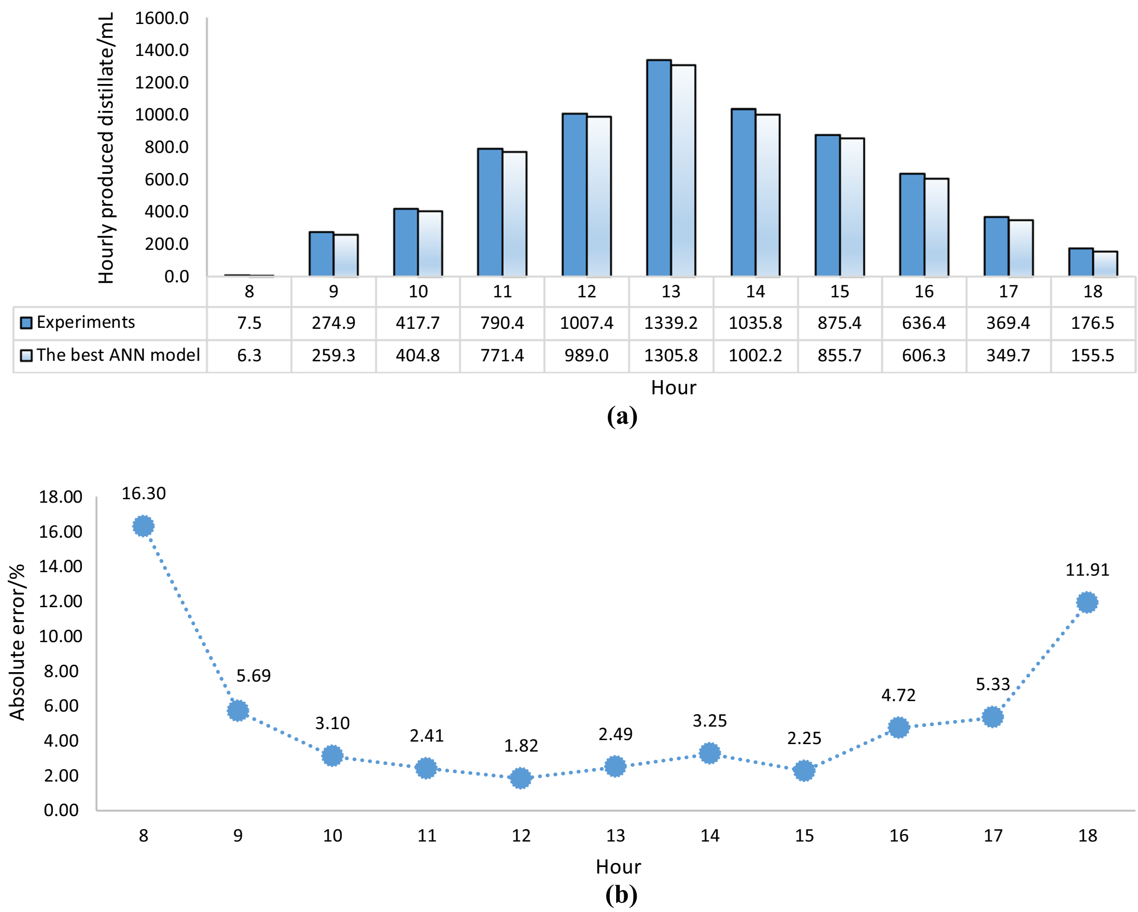

Fig. 3 Evaluation of the prediction ability of the best ANN model to estimate the produced distillate for each hour of the sample day, i.e., September 9, 2019, **a** the experimental and predicted values; **b** the absolute error

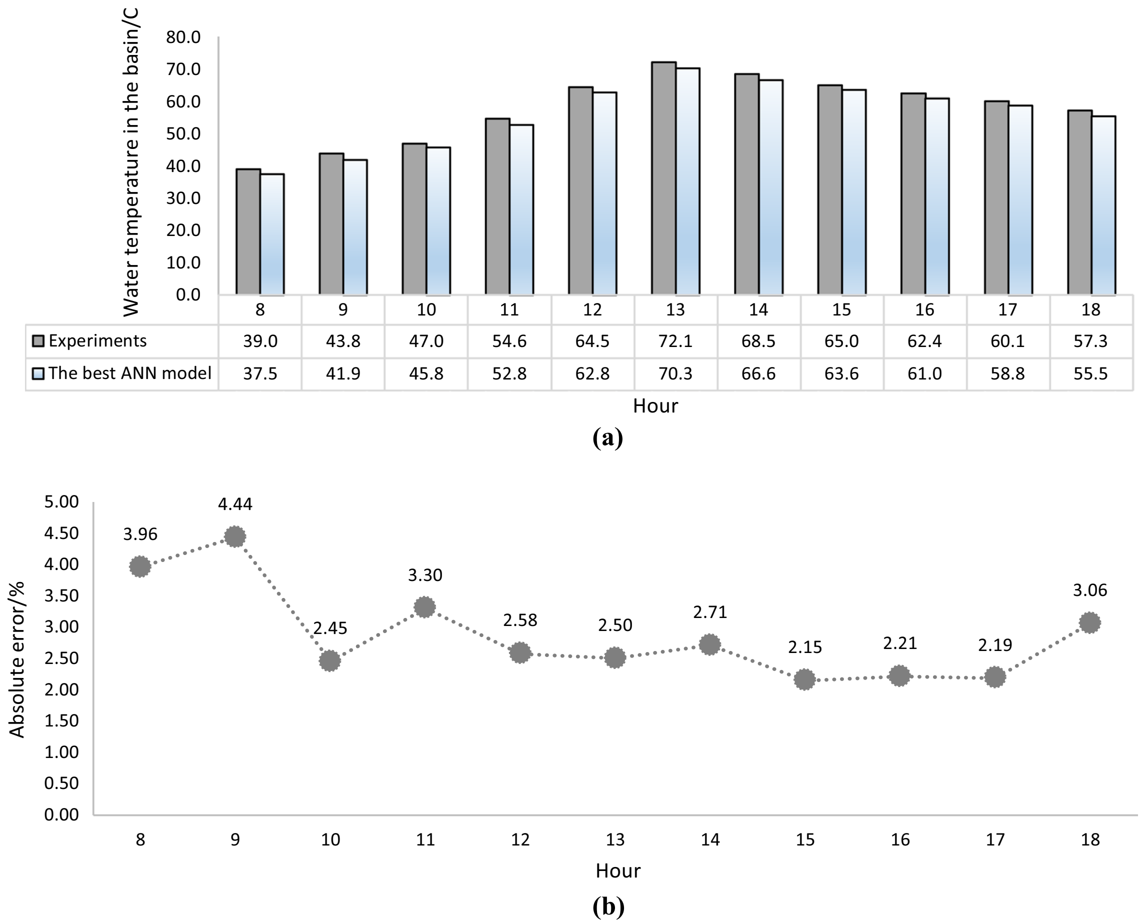

Fig. 4 **a** Evaluation of the prediction ability of the best ANN model to estimate water temperature in the basin for each hour of the sample day, i.e., September 9, 2019, **a** the experimental and predicted values; **b** the absolute error

As the examples, at 8, 13, and 18, the best ANN model predicts the water temperature in the basin 37.5, 70.3, and 55.5 °C, while the actual values are 39.0, 72.1, and 57.3 °C, respectively.

In order to provide a better outlook into the prediction accuracy of the best ANN models, the estimated and actual values of the cumulative distillate production are compared together for different hours of the sample day in Fig. 5a. Furthermore, the corresponding error profile is given in Fig. 5b. The information provided in Fig. 5 reveals that by passing more time from the beginning of the investigated time period, i.e., 8, the absolute error significantly declines and it approaches a constant level around noon. At 9, the absolute error is 5.63%, while it reaches more than half at 12, i.e., 2.64%, and after that it almost stays constant at that level. In addition, it is worth mentioning the values for 8 are so small that they are shown 0.00 L by two digits in Fig. 5a. However, they are not really zero and they have small values, and for that reason, the error for cumulative water production is not zero.

The obtained values shown in Fig. 5 demonstrate that the best ANN model to predict the hourly distillate is able to provide high accuracy for the daily freshwater production of the solar still. It estimates this criteria 6.70 L, while the experimental value is only 0.22 L more, i.e., 6.92 L.

Monthly performance of the foremost ANN models

In addition to September, for January, February, March, April, …, November and December, sample days are considered to evaluate the prediction ability of the best found ANN models during a year. For each month, a day had been kept, which was not fed into the developed codes to obtain ANN models. The average monthly error (i.e., the average for the sample day in each month) for the produced distillate and water temperature in the basin are reported in Figs. 6 and 7, respectively. In addition to these two profiles, the values of error in prediction of the daily water production are also given for different months of a year in Fig. 8.

The profiles depicted in Figs. 6–8 show that the error in the estimation of the hourly distillate production, water

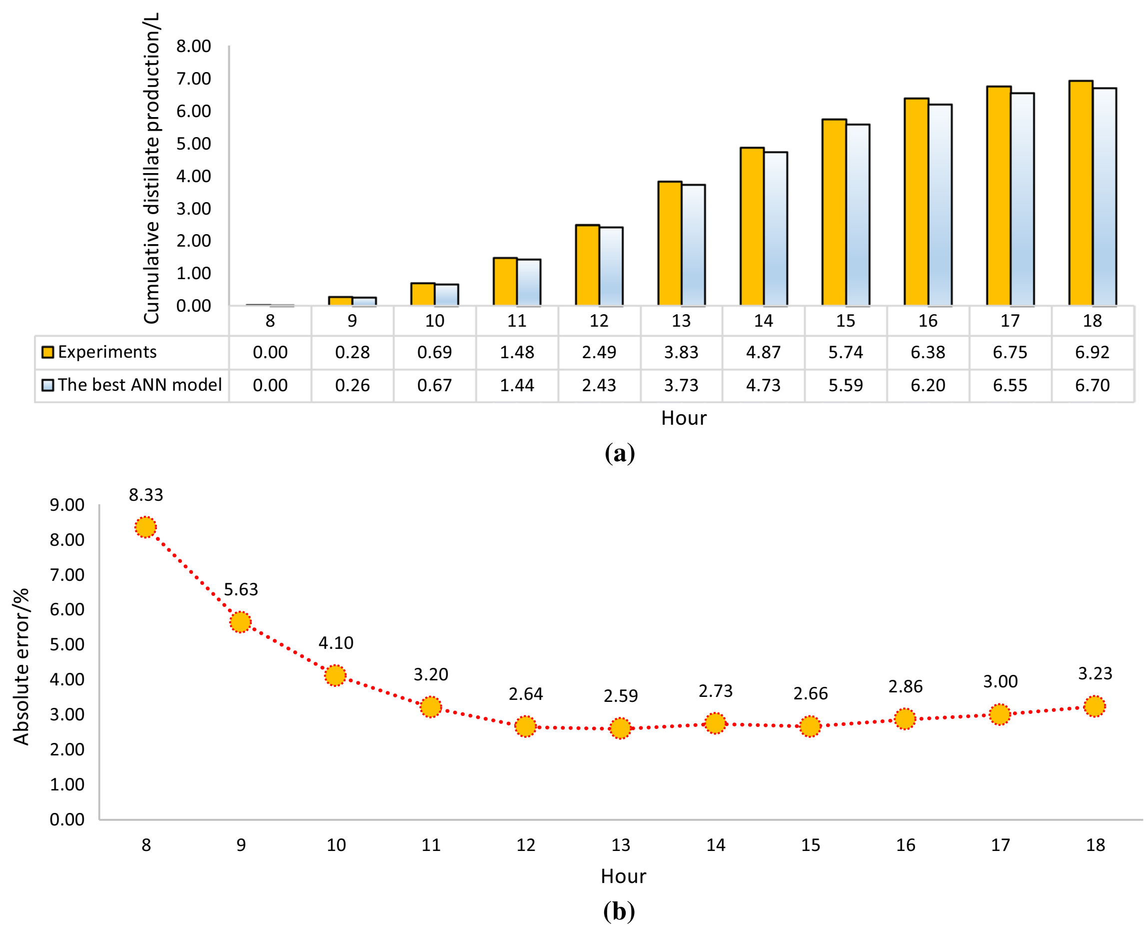

Fig. 5 **a** Evaluation of the prediction ability of the best ANN model to estimate the cumulative produced distillate for each hour of the sample day, i.e., September 9, 2019, **a** the experimental and predicted values; **b** the absolute error

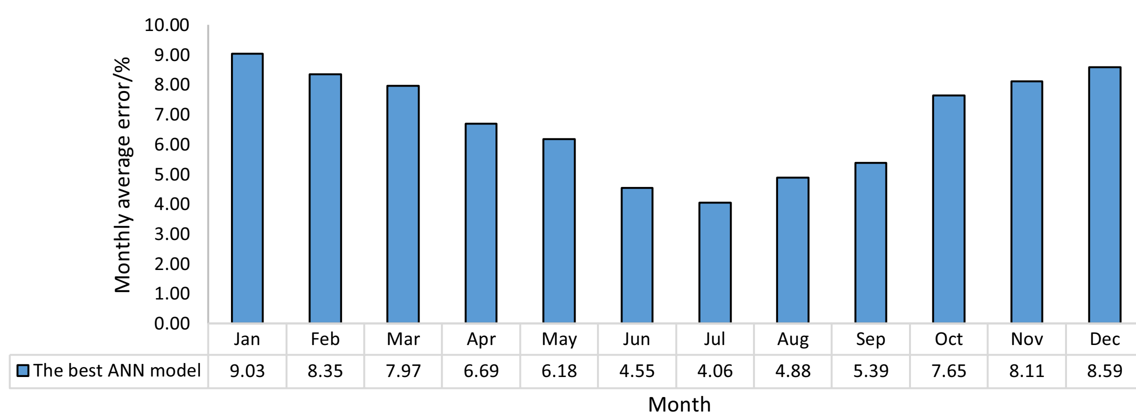

Fig. 6 Monthly average error profile for prediction of the hourly distillate production

temperature in the basin, and the daily freshwater production are in the ranges of 4.06–9.03%, 2.07–5.13%, and 2.41–5.84%, respectively. As a result, by employing the best found ANN models, it is guaranteed that the performance of the investigated solar still is predicted with less than 10% error, which is a considerable outcome. Additionally, for all the cases, the hotter temperature and

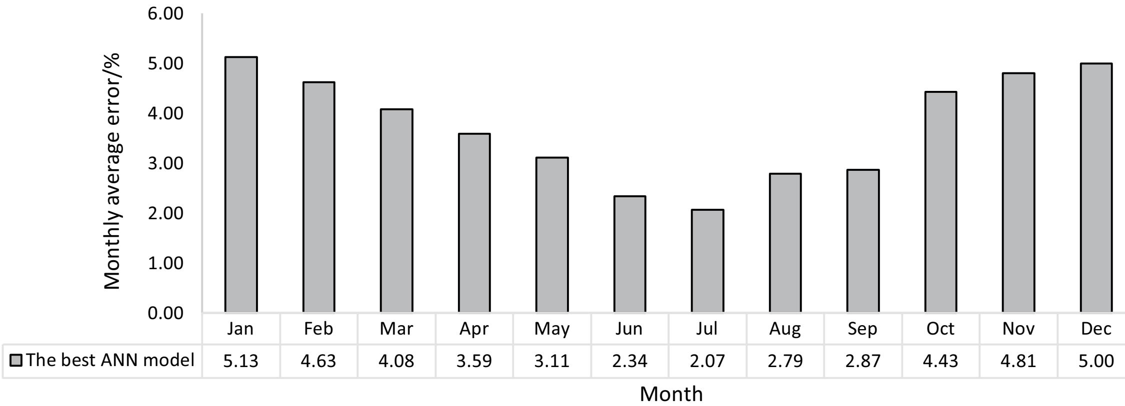

Fig. 7 Monthly average error profile for prediction of water temperature in the basin

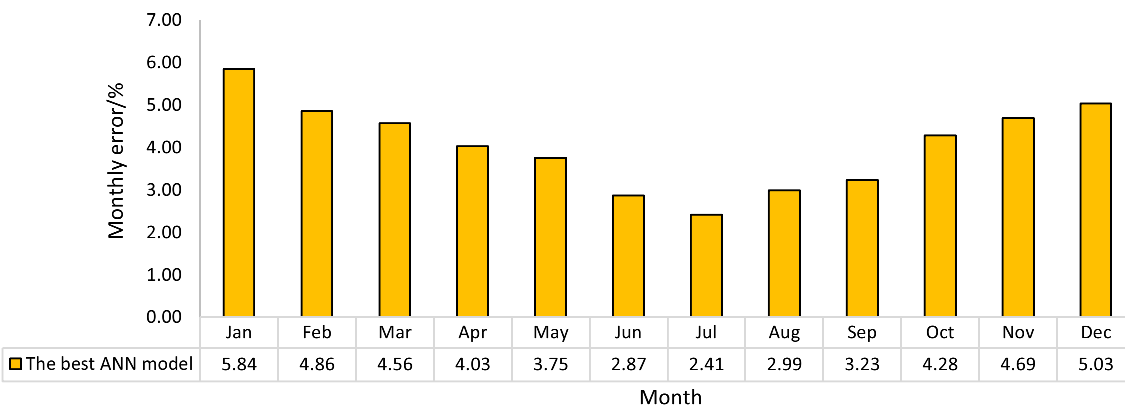

Fig. 8 Monthly error profile for prediction of daily water production

solar irradiance a month has, the more accurate the best ANN model works. July has the best precision, whereas the highest error is seen for January.

Conclusions

By taking advantage of obtained experimental data during a year, the performance of an enhanced design of a solar still system was simulated using artificial neural network (ANN) modeling approach. Three types of ANN, namely feedforward (FF), backpropagation (BP), and radial basis function (RBF) structures, were examined to find the best of them to estimate the hourly values of the freshwater production and water temperature in the basin.

It was found that FF and RBF types of ANN were the foremost ones to predict the hourly distillate production and water temperature in the basin, respectively. Therefore, because of different behavior of different performance of criteria in a solar still desalination technology, various types, and not only one structure, should be examined to obtain the highest possible prediction accuracy. In addition, the hourly and monthly evaluation of the prediction of the two mentioned criteria in addition to the cumulative distillate showed the potential of the best found ANN structures for accurate prediction of the performance criteria of a solar still. Therefore, application of them to reduce the computational time and cost of the numerical modeling approaches is highly recommended.

In addition, using the developed ANN models to find proper control strategies for the system and applying other ML approaches for modeling and comparing them with the results of this study could be suggested.

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