

Estimating the Annual Global Solar Radiation In Three Jordanian Cities by Using Air Temperature Data

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Abstract: Estimating solar radiation is an imperative requirement for solar energy development in Jordan. In this paper, a quantitative approach, based on Artificial Neural Network, was developed for estimating the annual global solar radiation of three Jordanian cities: Amman, Irbid and Aqaba. These cities are currently witnessing huge development and increasing demand for energy supply. Using a set of known meteorological parameters, two Artificial Neural Network (ANN) models with different architectures, called case 1 and case 2, fed with three types of learning algorithms for data training and testing, were designed to identify the optimum conditions for obtaining reliable and accurate prediction of the solar radiation. The results showed that model case 1 performed generally better in terms of predicting the annual GSR (96%) compared to model case 2 (95%). Furthermore, the algorithms LM and SCG in general, ensured the highest efficiency in training and testing the data in the designed models compared to the GDX algorithm. Therefore, model case 1, designed with one of these two algorithms, is selected as the optimal model design that is able to compute with high accuracy the annual solar radiation for the three studied cities.

تقدير الإشعاع الشمسي الكلي السنوي في ثلاث مدن أردنية باستخدام بيانات درجة حرارة الهواء

الصديق ابوالقاسم

الملخص: إن تقدير الإشعاع الشمسي من المتطلبات الضرورية لتنمية وتطوير الطاقة الشمسية في الأردن. تتناول هذه الورقة تطوير طرق تقدير كمية مبنية على أساس الشبكة العصبية التجريبية لتقدير الإشعاع الشمسي السنوي الكلي لثلاث مدن أردنية هي: عمان، وإربد و العقبة. حيث تشهد هذه المدن، حالياً، تطوراً هائلاً مصحوباً بزيادة كبيرة في الطلب على الطاقة. باستخدام بيانات مناخية معروفة. تم تصميم نموذجين للشبكة العصبية التجريبية ببناء مختلف سمياً الحالة 1 والحالة 2 تم تغذيتهما بثلاثة أنواع من الخوارزميات التعليمية بهدف التدريب والاختبار. ولقد صمما بهدف تحديد الحالات المثلى للحصول على بيانات إشعاع شمسي ذات موثوقية ودقة عاليتين. وقد أوضحت النتائج أن الحالة 1 قد أعطت نتائج أفضل من حيث توقع الإشعاع الشمسي الكلي السنوي بنسبة (96%) مقارنة مع الحالة 2

بنسبة (95 %) إضافة إلى ذلك، فإن كلا من الخوارزميات LM و SCG في العموم قد أكد على أعلى كفاءة في التدريب والاختبار للنماذج المصممة مقارنة بالخوارزمية GDJ. عليه فإن نموذج الحالة 1 والمصمم بإحدى الخوارزميات قد اختير كنموذج امثل قادر على حساب الإشعاع الشمسي الكلي السنوي بدقة عالية في كل من المدن الثلاث تحت الدراسة..

Keywords: artificial neural network, global solar radiation, modeling, algorithm

1. INTRODUCTION

Jordan is a sunny country near the Mediterranean region with average 3000 hours of solar irradiance per annum. Due to its position within the solar belt of the world where average solar radiation ranges between 5 and 7 KWh/m², Jordan in theory has a potential of at least 1000GWh per year, making the country an ideal location for solar power generation (Zafar 2012) [1]. Despite this solar ampleness, Jordan in fact has poor energy status and is heavily reliant on imported energy, mainly from oil rich states which accounts for 96% of its energy needs (NERC 2005) [2]. As the country is growing in population, economy and urbanization, and therefore, increasing per capita consumption, the complete reliance on foreign energy imports places a heavy burden on the government's budget and deters the socio-economic advancement of Jordan citizens. Providing energy security and reducing overexposure to foreign imports have been for long urgent priorities topping the agenda of the successive governments in Jordan. Driven by the escalating prices of imported fossil fuels and the associated risks of pollution and disruptions in supplies, Jordanian officials have been rethinking to shift towards boosting the contribution of domestic renewable energy sources to the national energy supply (Hrayshatand Al-Soud 2004) [3]. In its 2007 National Energy Strategy, the Jordanian government unveiled its intention to increase reliance on domestic energy sources from 4% to 40% by the end of year 2020. The renewables will account for 7% of the total energy mix by year 2015; of which, solar will provide the biggest contribution (Zafar 2012; IEA 2011) [1], [4]. As a result, optimization measures, investment policies and streamline processes have been revolutionized to develop solar resources as a practical, clean, cost-effective and sustainable solution.

A successful implementation of solar projects relies basically on proper characterization of the prevailing solar conditions in the proposed site. There are diverse approaches used for characterizing solar radiation variables, be they experimental or mathematical-based methods. However, experimental methods bear several operational and financial requirements compared to mathematical methods. In less economically developed countries, like Jordan, the assessment of solar radiation encounters several problems, such as: lack of technical and financial resources, shortage of solar data and wide areal coverage. To overcome the shortcomings, scientists and engineers develop sophisticated mathematical models to estimate solar radiation with minimum error and high certainty. Therefore, using appropriate prediction model can be a practical, time- and cost-effective alternative solution to Jordan to ensure high performance and trusted scheme of assessment.

In mathematical approaches of solar assessment, various types of environmental information, such as weather, climate, location and time, are routinely involved in the characterization process. However, the fluctuation nature of these environmental parameters affects the model sensibility and ability to quantify global solar radiation accurately. Unveiling the relationship between these variations and the amount of GSR would help the analyst in designing the optimum conditions of a model that ensure attaining the best estimation with minimum errors and high efficiency. In this paper, an estimation modeling using the stochastic method of artificial neural network (ANN) was developed and applied for characterizing the global solar radiation (GSR) for three main cities in Jordan that are experiencing intensive development and human settlement - Amman, Irbid and Aqaba cities. The objective is to identify the best ANN model requirements that

ensure optimized estimation of GSR for the whole of Jordan.

2. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network (ANN) is an emulation of biological neural system. It has a specific architecture that determines the way it works on data. A typical ANN structure is composed of three layers of neurons that store data: a layer of input neurons is connected to a layer of hidden neurons, which is connected to a layer of output neurons. The synapses connecting between the neurons transport information from one sending to one receiving neuron. The linkages are represented by weights that store knowledge and guide the flow of information through the network (Lillesand and Kiefer 2000) [5]. Based on the topological structure of the network, node characteristics, learning or training algorithms, different ANN classes (models) can be generated, such as: back-propagation neural network (BPNN), multilayered neural networks (MNN), multilayer perceptron neural network (MLPNN), radial basis function neural network (RBFNN), neural network ensemble (NNE), evolving polynomial neural network (EPNN) and others. These models generally perform tasks that linear models cannot do, and they do not require a prior knowledge from the analyst on the nature of relationship between input and output variables (López et al. 2001) [6]. Because they exhibit robustness, parallel architecture, fault tolerant capability and the ability to work as universal function approximators, ANNs are profoundly used in solving complex science and engineering problems (Cybenko 1989) [7] and in understanding phenomena of multidimensional information domain (Haykin 2009) [8]. Experience from studies dealing with solar energy assessment indicates to the preference of ANN approach over other empirical statistical approaches in forecasting the solar radiation over time domain (Jiang 2009) [9].

In the practice of GSR modeling using ANNs, analysts use a host of datasets characteristic to the investigated site, in order to train, run and validate

the neural network, such as: meteorology, climate, time scale and surface geometry data. However, meteorological measurements are easily accessible from national meteorological agencies, and they are widely used to estimate the global solar radiation in many research works. For example, Tadros (2000) [10] used sunshine duration variable to estimate the global solar radiation over meteorological stations in Egypt; while Bakirci (2009) [11] and Almorox et al. (2004) [12] used it for estimation of global solar radiation in Turkey and Spain, respectively. Kalogirou et al. (2002) [13] estimated the maximum solar radiation using measured values of air temperature and relative humidity as input in ANN. Rehman and Mohandes (2008) [14] have employed data combination of day of year, time day of year, air temperature and relative humidity in ANNs for the estimation of global solar radiation for Abha city, Saudi Arabia. The researchers found that temperature and relative humidity, specifically, helped successfully the neural networks in estimating GSR, and that ANNs can be used to predict GSR for locations where only temperature and relative humidity data are available. In another study in Saudi Arabia, Tasadduq et al. (2002) [15] utilized the full year data of hourly values of ambient temperature in Jeddah City to train a neural network model for the prediction of hourly mean values of ambient temperature 24 hours in advance.

3. WEATHER DATA

In this study, Amman datasets of weather measurements collected from meteorological stations for five years were used in estimating and characterizing the global solar radiance. The outcomes of modeling Amman's solar data were extended for the whole Jordan. Initially, the collected information included: (1) global solar radiation, which ranges between (0.7930) and (0.0540), (2) sunshine duration which was between approximately (0.0000 hour) and (0.9200 hour), (3) maximum (39.9 °C) and minimum (-4.8 °C) air temperature, and (4) relative humidity, which was between approximately (13 %) and (98 %). The global solar radiation component was measured by a pyranometer.

4. MODEL DESIGN & IMPLEMENTATION

In this study, a simple multi layered feed forward perceptron ANN model was selected and developed in MATLAB environment with a customized Graphic User Interface (GUI). Two sorts of this model were designed, called model case 1 and model case 2. Both of them estimate solar radiation by computing the clearness index. In each model, the network architecture was built on the basis of layer configuration of 1-2-1 (i.e. 1 input layer, 2 hidden layers, and 1 output layer), as shown in Figure 1. The input layer stored data of sunshine ratio, temperature and relative humidity, while the output layer stored data of clearness index. The learning algorithm of error back propagation was used to determine the interconnecting weights between neurons. The two configuration patterns (models) of training, called case (1) and case (2), were used and presented to the network as the following:

$$\text{ANN model (case 1): } (S/S_0) + (T_{\min}/T_{\max}) + (h) = (H/H_0) \dots\dots\dots (1)$$

$$\text{ANN model (case 2): } (S/S_0) + (T_{\min}/T_{\max} - T_{\min}) + (h) = (H/H_0) \dots\dots\dots (2)$$

where (H/H_0) represents the clearness index, such that H = solar radiation and H_0 = maximum solar radiation (Mishraa 2008) [16], (S/S_0) the sunshine ratio, such that S = sunshine duration and S_0 =maximum sunshine duration; (T_{\min}/T_{\max}) the temperature ratio, such that T_{\min} =minimum temperature and T_{\max} = maximum temperature, and (h) the relative humidity.

As noted above, the difference between the two models lies in the function of temperature. This is because temperature exhibits a marked seasonal variation due to periodicity in the earth's orbit about the sun. For this reason, temperature variations can be represented using mathematical cyclic functions [17]. This procedure allows not only to have an optimal learning but also to know the effect of temperature on the daily GSR prediction. Morid et al. (2002) [18] estimated the GSR in Iran using temperature based approach and found that this approach was capable of generalizing the results

and feasible when climatological data are rare.

The collected meteorological data from Amman City were used for training, validating and testing the designed ANN; such that, training dataset (data of input and output layers) composed 80% while validation and testing dataset composed the remaining 20%. In the training process, neurons were trained and adjusted using error back propagation algorithm. The training parameters were set as the following: Epochs of training were set to: 10,000, Training goal was set to 10⁻³, Maximum time of training the network is depending on the learning algorithm, Momentum constant =0.92, number of neurons=[30 15 1]. In order to suit the consistency of the model, input and output data were firstly normalized in the (0, 1) range and then returned to original values after the simulation using the following formula:

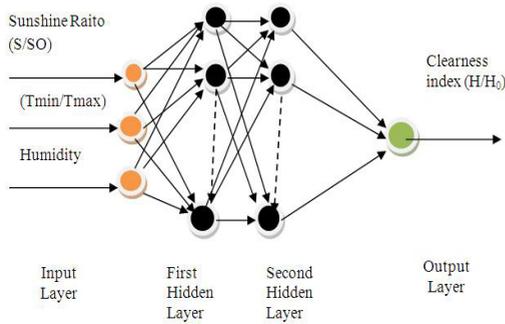
$$P' = (P - P_{\min}) / (P_{\max} - P_{\min}) \dots\dots\dots (3)$$

Where P is inputs or outputs of the network, P' is normalized inputs or outputs of the network. The value of normalized input or output is 1 when the input or output is P_{\max} , and the value of normalized input or output is 0 when the input or output is P_{\min} .

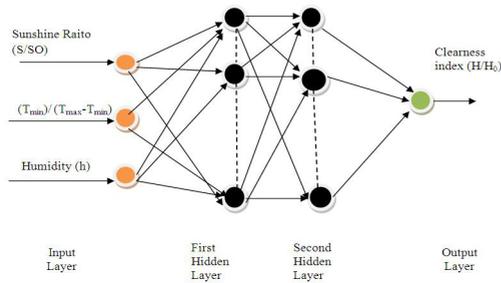
In the learning process, three learning algorithms of Levenberg-Marquardt (LM), scaled conjugate gradient (SCG) and gradient descent with momentum (GDX) were embedded in the ANN architecture. The applied models were used to estimate global solar radiation for Amman City (case 1 and case 2) while for Aqaba and Irbid cities, model case 1 was applied.

The sigmoid function was applied in the designed ANN; such that "Tansig" transfer function was used in the hidden layer and "Purelin" transfer function in the output layer.

The estimation of solar radiation was performed by multiplying the resulted value of clearness index (calculated from each model case in MATLAB) by the extraterrestrial solar radiation intensity at normal incidence (Mishraa et al. 2008) [16].



(a) Model Case 1 Architecture



(b) Model Case 2 Architecture

Figure (1). Two suggested configuration patterns of ANN structure: (a) model case 1 and (b) model case (2), used in training and testing the ANN

5. MODEL VALIDATION

The performance of each ANN model type in estimating the solar radiation was validated by comparing the predicted value resulting from training and testing the data with the true (measured) data. This was done with the aid of two assessment tools:

1. The mean square error (MSE) tool, measured by the following formula:

$$MSE = \left(\frac{1}{N}\right) \sum_{i=1}^N (X_{estimated} - X_{measured})^2 \dots (4)$$

where N is the number of input-output pairs, X is the measured or estimated value of the output.

2. The efficiency (EFF) tool, measured by the following formula:

$$\text{Model Efficiency} = 1 - \left\{ \frac{\text{MSE}}{\text{variance}} \right\} \dots (5)$$

where variance equals the square of standard deviation. $\{(STD)^2\}$

The best model that gave the lowest errors (MSE) and best fit of (EFF) was selected as the stable, suitable model for estimating solar radiation. In addition, the performance of each learning algorithm was assessed; such that, the algorithm that shows minimum error (MSE) and maximum efficiency (EFF) during training and testing stages is the best algorithm to select for working the ANN model.

6. RESULTS & DISCUSSION

Figure 2 illustrates the results of GSR modeling in ANN model case 1 and case 2 for Amman City; while Figure 3 illustrates the results of GSR modeling in model case 2 for Aqaba and Irbid cities when fed with the three learning algorithms of LM, SCG and GDX, respectively. All of the prediction data for the three cities showed generally excellent accuracy when plotted against the measured data.

Table 1 summarizes the performances of prediction in models case 1 and case 2 during training and testing stages for Amman City. The table shows that the average testing accuracy of model case 1 was 0.9608, a little higher than that of model case 2 (0.9516). All the test efficiency values were positive; making both models logically accepted. However, the assessment of the overall performance of the designed ANN models in predicting the annual GSR for Amman City, as shown in Figure 4, reveals that model case 1 had excellent performance (< 96%) compared to model case 2 (< 95%). This implied that variations in temperature calculated in case 1 have influential effect on predicting the annual variations of GSR. Consequently, ANN model case 1 can be selected as the optimal model suitable for evaluating the annual GSR for Aqaba and Irbid cities as well as the whole Jordan.

There are some remarks that can be made on

the performances of the three learning algorithms during training and testing stages. Using model case 1 in modeling Amman data, the average testing efficiency of the model was(+0.9608) and that the learning algorithm of LM had the lowest MSE

(8.9144e-004) and highest efficiency (+0.9854) compared to other algorithms. GDX has the highest MSE (+0.0035) and the lowest efficiency (+0.9423) and SGD is between that.

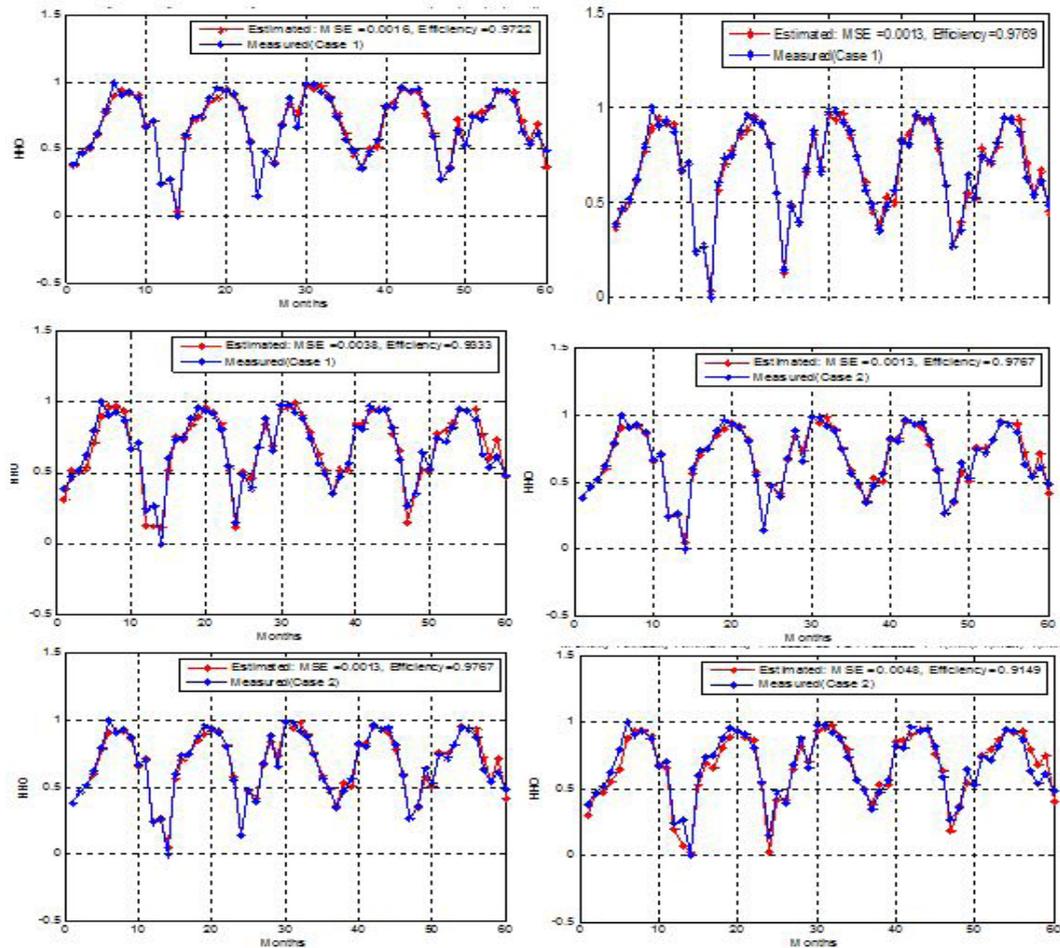


Figure (2). Results of Case 1 and Case 2 modeling of GSR for Amman City using LM, SCG and GDX learning algorithms, respectively

Using model case 1 in predicting the annual GSR for Aqaba and Irbid cities (Figure 3), the results showed generally excellent accuracy when plotted against the measured data. Table 2 summarizes the performances of training and testing efficiencies of the ANN model case 1 for the two cities. From the graph and cross-validation report, it was noticed that for Aqaba City, the average testing efficiency of the

model was(+ 0.9103) and that the learning algorithm of LM had the lowest MSE (0.0183) and highest efficiency (+0.9363) compared to other algorithms. GDX has the highest MSE (+0.0100) and the lowest efficiency (+0.8775) and SGD is between that. For Irbid City, the average testing efficiency of the model was (0.8630) and that the learning algorithm of LM had the highest MSE (0.0183) and lowest efficiency

(+0.8028) compared to other algorithms. GDX has the lowest MSE (+0.0063) and the highest efficiency (+0.9324) and SGD is between that.

In general, the results of ANN modeling

suggest that model case 1, when fed with either learning algorithms of LM or SCG, is the optimum model that ensures best performance and reliable assessment for predicting the annual GSR for the three studied cities.

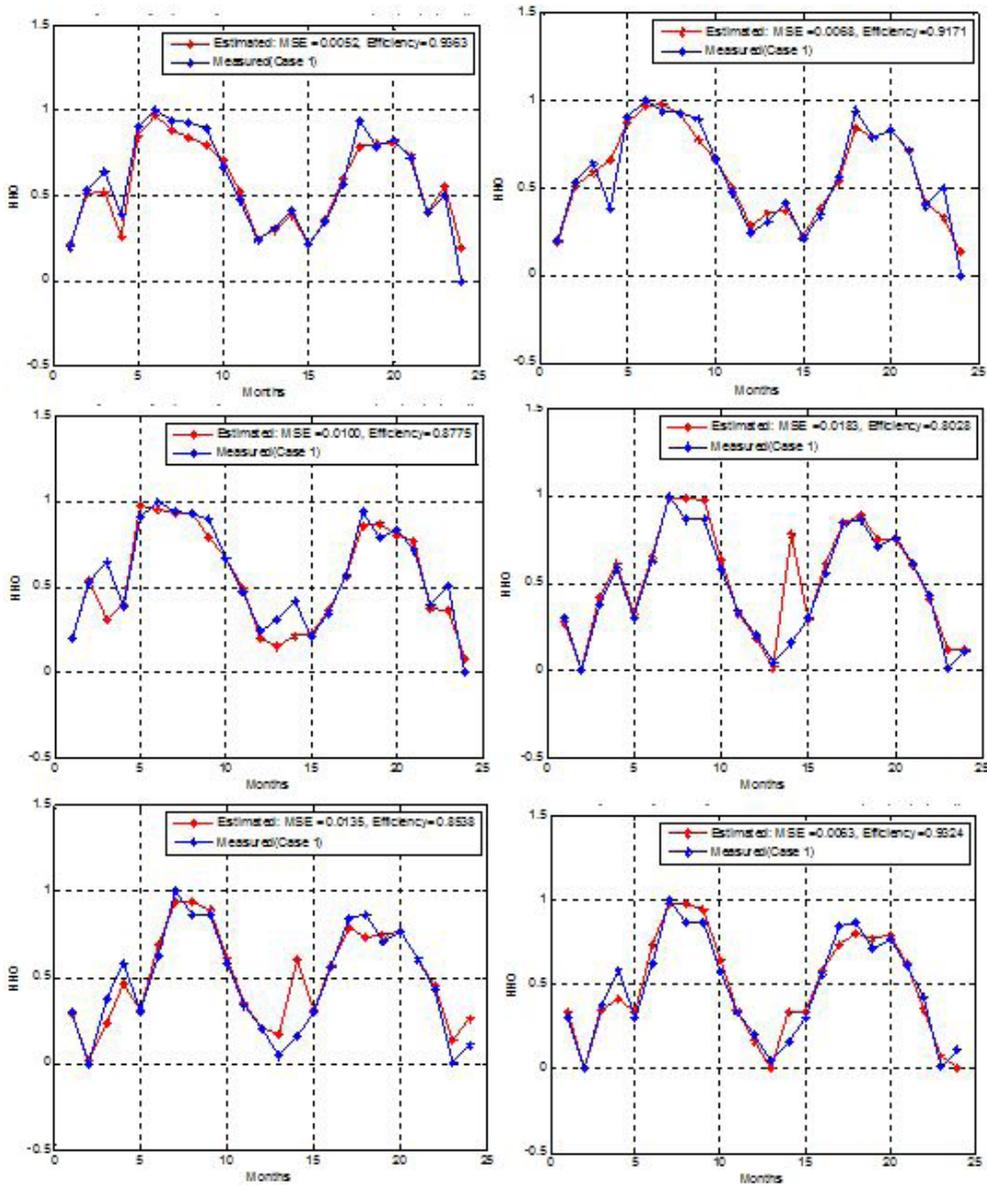


Figure (3). Results of Case 1 modeling of GSR for Aqaba and Irbid Cities using LM, SCG and GDX learning algorithms, respectively

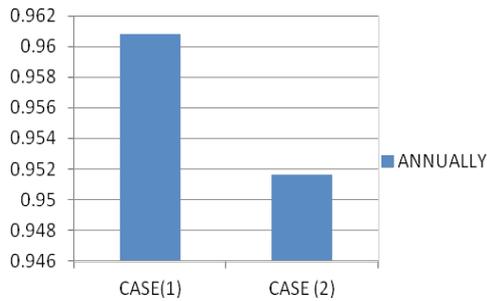


Figure (4). Comparison between the testing efficiencies of ANN models case 1 and case 2 selected to predict the annual GSR for Amman City

7. CONCLUSION

The ANN models of case 1 and case 2 developed in this study have shown success in evaluating the annual variations in global solar radiation for Amman City based on the solar parameters measured during 5 years. In general, the two

models showed similar patterns of good to excellent efficiency in predicting the annual variations of GSR. However, the validation reports indicated that model case 1 performs generally better than model case 2. This can be attributed to the outstanding capabilities of model case 1 in sensing the annual fluctuations in solar conditions and in reducing the error between measured and estimated data to a minimum level; hence, improving the prediction accuracy. This finding leads to the preference of using model case 1 in predicting GSR for Aqaba and Irbid cities. The results for both cities illustrated the high capability of model case 1 in predicting the annual GSR. In addition, the accuracy and efficiency of modeling increase significantly when using the learning algorithms of LM and SCG in the ANN structure. Therefore, when designed with one of these two learning algorithms, model case 1 can estimate the annual global solar radiation for the selected Jordanian cities with high accuracy and reliability.

Table (1). Cross-validation report of ANN modeling results of case 1 and case 2 (annual GSR) for Amman City

[30 15 1]	Model Case 1				Model Case 2			
	Training		Testing		Training		Testing	
	MSE	EFF	MSE	EFF	MSE	EFF	MSE	EFF
Train LM	8.9144e-004	0.9854	0.0016	+0.9722	8.7935e-004	0.9856	0.0013	+0.9767
Train SCG	9.9410e-004	0.9837	0.0013	+0.9769	9.9997e-004	0.9984	0.0013	+0.9767
Train GDX	0.0035	0.9423	0.0038	+0.9333	0.0046	0.9241	0.0048	+0.9149
Average				+0.9608				+0.9516

Table (2). Cross-validation report of ANN modeling results of case 1 (annual GSR) for Aqaba and Irbid

[30 15 1]	Aqaba City				Irbid City			
	Training		Testing		Training		Testing	
	MSE	EFF	MSE	EFF	MSE	EFF	MSE	EFF
Train LM	9.4137e-004	0.9878	0.0052	+0.9363	9.7916e-004	0.9909	0.0183	+0.8028
Train SCG	7.1036e-004	0.9908	0.0068	+0.9171	9.3328e-004	0.9874	0.0135	+0.8538
Train GDX	9.6942e-004	0.9874	0.0100	+0.8775	0.0030	0.9593	0.0063	+0.9324
Average				+0.9103				+0.8630

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