Prediction of the Power Output of Solar Cells Using Neural Networks: Solar Cells Energy Sector in Palestine

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Abstract

The prediction of the output power of solar cells in a given place has always been an important factor in planning the installation of solar cell panels, and guiding electrical companies to control, manage and distribute the energy into their electricity networks properly. The production of the electricity sector in Palestine using solar cells is a promising sector; this paper proposes a model which is used to predict future output power values of solar cells, which provides individuals and companies with future information, so they can organize their activities. We aim to create a model that able to connect time, place, and the relations between randomly distributed solar energy units. The system analyzes collected data from units through solar cells distributed in different places in Palestine. Multilayer Feed-Forward with Backpropagation Neural Networks (MFFNNBP) is used to predict the power output of the solar cells in different places in Palestine. The model depends on predicting the future produce of the power output of solar cell depending on the real power output of the previous values. The data used in this paper depends on data collection of one day, month, and year. Finally, this proposed model conduct a systematic process with the aim of determining the most suitable places for an installation solar cell panel in different places in Palestine.

Keywords: Neural Networks, Solar Cell Energy, Prediction.

1. INTRODUCTION

Society starts searching for other energy resources with more awareness of their responsibility to the environment. Renewable energy experiences a huge expansion, which raises many challenges to the scientific and technical community [1]. Renewable energy is a clean and inexhaustible energy, and it's technology is developing rapidly [1]. In recent years, solar cells increasingly used to produce the energy in Palestine, one of the problems faced are the unpredictability in their production, since they depend on climatic variables of each moment [2]. Currently, distribution companies are responsible for managing and selling the energy into their networks. Palestine has seen an increase in the number of solar parks. The current Palestinian society aims to reduce electrical energy dependence, a better use of resources and greater awareness of the environment. There have been many initiatives in Palestine by the directives of support measures, renewable energy, establishing growth targets for renewable technologies in order to get more energy production comes from these resources [3]. Solar energy is the energy produced by thermonuclear reactions continuously on the surface of the sun, this energy spread in the universe with different energy forms such as light, heat, x-ray, and ultraviolet, these forms of energy forms the solar spectrum. The solar energy is a vital factor of life on the earth, solar spectrum hits the earth with half of its energy level because of the atmospheric shield and the reflection of the energy of the earth's surface, and this energy can be used in different fields like agriculture, heating, cooking, and electricity production [4, 5]. One of the major solar energy usages is to produce electricity, the process that can perform mainly in two methods, thermal solar energy which depends on heating fluids in pipe network running turbines to produce electricity, and photovoltaic solar energy, which uses photovoltaic phenomenon to produce electricity directly from the sunlight [6, 7].

In recent years, solar cells have a deployment unprecedented. The total energy supply from solar cells in Palestine in the year 2007 accounted of 1402 ktoe. The indigenous production contributed 19% of total primary energy supply while the remaining quantity imported from Israel [3]. Solar cell power in Palestine is a natural wealth, which must be explored; the electric distribution companies receive the electricity in its electrical network from two resources; the direct electrical lines from Israel and the solar cell panels installed in some areas in Palestine. There are no plans or estimation process, which used by these companies to determine the demand and the production of solar cells in such place, so the prediction of solar cell output power in such place, will help the company to plan and manipulate the electricity in this area, which will produce stability in electrical connection. For many years, they have tried to learn how to predict future events, so that, they can take preventive action. weather conditions are one of the future events, which directly or indirectly affect us every day, especially in electricity consumption. Therefore, they have developed methods of climate prediction, supported by different models to predict solar cell output power using mathematical prediction systems [8].

In general, a lot of researches have been developed for this purpose, but the most of them, use statistical methods to get results and historical analysis for the collected energy, without using prediction and classification models in order to create a solar energy map, that shows the best regions and provide an advice for people who are concerned in the energy field. In [9] the author used artificial neural network (ANN) control algorithms applied to the solar energy prediction, they proposed an algorithm detects the optimal operation point for photovoltaic and thermal panels by studying the (PV/T) model behavior considering irradiation and ambient temperature. Another related study was made to determine the highest time horizon for generating solar energy prediction by Ercan Izgi et al [10], they used small solar power system application to study and predict the time horizon by dividing the study period of time into short term [5min] in medium term in April, and [3 min] for short term, [40 min] for medium term in August, during April and August RMSE between the measured value and testing value changed between 33-55 in April and 37-63 in August , ANN algorithm used to predict the electricity generated in period 30-300 minutes. The external weather conditions that affect the solar energy generation are studied by Esteban Velilla and others in [11], they used two modules of solar cells [mono-crystalline (55w) and organic solar module (12.4w), the factors monitored by this study are the temperature, relative humidity, and irradiance, that are used as inputs for an ANN algorithm, which developed by the team to train ,validate and test the electric power generated, the result obtained of solar energy produced using organic solar module was better than mono-crystalline module in the extreme conditions of (high temperature, high humidity, and lower irradiance). Electricity sector in Palestine was studied by Ayman Abu AlKher in [12] and others, the study has been divided in two parts, one part to study the current situation of electricity production, consumption, and transmission, the second part is a comparison between Palestine and other neighbors, to highlight the electricity consumption gap, and he used a mathematical and economical model to predict the relation between electricity consumption and economic growth. Solar radiation forecasting study made by Bader M. Alluhaidah and others [13] explained the most effective variables that are used in the solar forecasting process as inputs for ANN, the case study was made in Saudi Arabia. The simple structure offers better results in terms of error between actual and predicted solar radiation values. A method for modelling and prediction of PV-generated power [14] has been developed by Amin Mohammed Sabrian et al, this method uses two kinds of ANN, general regression neural network (GRNN) and feed forward back propagation (FFBP), in the modelling process, he used four inputs for both ANN (max temperature, min temperature, mean temperature, and irradiance) with the power as an output. The data were collected through 5 years from 2006 to 2010 period, it was split into two parts, first 3 years data used for training and 2 years data used for testing, the result in both methods give good results, where FFBP has better performance than GRNN.

One common method for data collection is the using of special data acquisition system based on the wireless sensor network, this method of data collection uses the wireless sensor network connected by Wi-Fi or Wi-Max technologies, to achieve a reliable connection between far sensor nodes [15]. The other useful method is using the local electricity providers, where they have a very useful projects for solar cells energy. They provided us with a very good amount of data that we can use as a start point in our prediction and classification model, we get solar cells values from Al Ojah village in the East, Al-Zababdeh village in the north, and Ramallah city in the middle of Palestine. Another way of collecting previous data is the used of the data in the website "Solar GIS", which is a website that integrated with satellites, google maps and other measurement tools, to measure and estimates the atmospheric variables like temperature, humidity, and solar irradiation, that are the main factors which affect the solar energy production all over the world. The general objective of the proposed model is to develop a system based on Neural Networks (NN), which can predict the short-term values of an output power of solar cells over days, months and one year. Which aims to help companies in planning, managing and forecasting the suitable time and place for the energy production from solar cells. The data used for the process of learning in this model was taken for one year (one value in each 5 minutes) from different locations in Palestine, which allow a possible approximating value of the total power acquired by solar cells. In another hand, it analyzes the behavior of the time series that determine the value of solar cells in one year for different cities of Palestine.

2. ARTIFICIAL NEURAL NETWORK

Supervised NNs depend on the provided input data, this data will be processed using special activation functions, with the final goal of producing output. The current output of the NN will be compared with the desired output for the purpose of training the NNs by updating the weights in each epoch, which produce decreasing in approximation error. Artificial neurons are elements with an internal state that changes depending on the signals it receives, such neurons also have a transition function, which allows them to change the level of activation signals received from neurons, whether connected or from the outside [16]. NNs have a basic structure consisting of a series of entries that reach the neuron, and one or more output are connected to the input of another neuron network, this structure is known as a multi-layered NN [17] as shown in Figure 1.

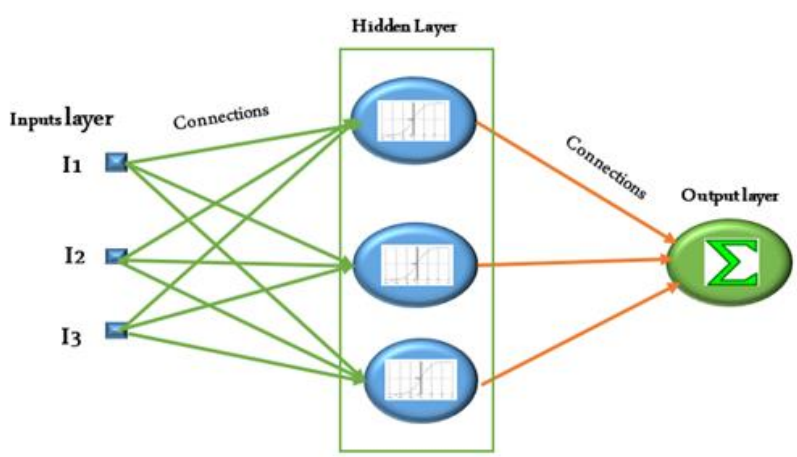

FIGURE 1: Basic Topology of Neural Network.

This type of structure has; an input layer which consists of input patterns. The connections in the hidden layer which are weighted connections between the input layer and the hidden layer, a processing units called neurons receives the input data from the input layer and processing it depends on the activation function, finally the output layer that is used to calculate the output of the NN. NNs are able to learn from input/output data to predict future value. Knowledge of this value can be performed in a time step, which is obtained from samples available at time t, and it can generate a value for time t + 1. It is also possible to predict multiple time steps, which involves taking other values known as the predicted values to generate new future value, NNs play good rule in time series prediction.

The general main steps for the basis NN start by a collection of the data to be used in training, validation, and testing. Preprocessing of the data which is an important stage that increases the performance of the NN, and reduces the number of processors (neurons) required, this will lead to reduce the number of neurons, and give the best curve fitting. Initialization of the NN starts by assigning values for the input weights, this process that most likely done randomly, or using certain algorithms according to the problem. In the NN training process, the activation function is applied to find the relation between the inputs and the outputs, and then updating the weights using the specified algorithms with a number of training data in order to get the best results. To check the validation of the NN, this model uses another set of data called validation data. Finally, the generalization process tests the NN for random and different dataset [17]. The Solar cells output power prediction using silicon cells is affected by several factors like solar irradiation, climate, temperature, relative humidity, dusty weather, cell direction, and the efficiency loss by the time [6]. In our proposed model we will use historical values of the solar cell output power recorded for a period of time (one year), the output values are recorded in (5 min) time horizon, this output power generated and recorded from the target output of the ANN [18].

In order to design the proposed NN, we must identify the problem domain and the factors that affect or determine the problem, it's known that the time series prediction is one of the most complex of the real world application, and it's also well known that the ANN has a good property of solving such complex problems. The training process is the mapping process between the input/output data of the NN when the input patterns provided to the NN with initial weights, the output of the NN are given by the following expression:

$$y_i = f\left(\sum_{j=1}^{m} w_{ij} x_j + b_i\right) \qquad 1$$

Where W_{ij} is the weights connection, and X_j are the value of the ith inputs for a simple of the NN, b_i is the NN bias, m is the number of neurons and f is the activation function. The general approximation criterion which uses to determines the improvement of the prediction process, is the error result, which comparing the actual output of the NN with the desired output in the learning process, this error is basically calculated using the following expression:

$$Er = y_{id} - y_{ia} \qquad 2$$

Where y_{id} is the desired value of the output for each ith element and y_{ia} is the actual value of the ith element, normally this criterion is used as a termination condition to stop the prediction process. In this paper, we use the root mean square error which presented by the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{id} - y_{ia})^2}{n}} \le \theta \qquad 3$$

Where n is the number of the input data, and Θ is the threshold value of the prediction process. The training process continue to adjust the weights until the error criteria are satisfied, the weights updated is performed by the equation 4:

$$\Delta w_{i+1} = \alpha.\ RMSE.\ x_i \qquad 4$$

Where α is the learning rate.
One advantage of the multilayer perceptron neural networks (MLPNN), is that it can predict any time series function if a configuration and an adequate number of neurons in the hidden layers are

available. The MLPNN is an excellent time series prediction, although it is impossible to find a single configuration for each application. The learning process of the MLPNN with backpropagation algorithm is not fixed to any application; a successful method is to try different settings until you get the desired response. The choice of training patterns is performed depending on the explicit needs of the prediction, which will show on the output and the quality of information available. Any changes in the patterns of training require different training parameters of the NN, but the training process remains the same.

3. METHODOLOGY

Developing a methodology to establish prediction is a relationship as accurately and precisely as possible. The values of future solar cell energy output require the knowing of the previous solar cell energy output, these values are used as input to the model, $x_t = F(x_t, \ldots, x_{t-tw}) + \varepsilon_t$, where x_t is the forecasting forward steps with respect to time t, F is the modeling function between the previous and future values, ε_t is the modeling error. Predicting of solar energy output can be performed using different techniques as; prediction by numerical models, prediction by statistical methods, time series prediction based on the application of statistical techniques linear and nonlinear, and prediction coefficient cloud cover from satellite images. Obtaining a final prediction model of solar energy output based on the time series prediction using NNs. Predicting the energy output of solar cell using only numerical models has a high bias and a high mean square error, which depends on the distribution function of the radiance data for the station (at positions predominantly clear sky conditions with errors are smaller). For this reason, we used Multilayer feed- forward with backpropagation neural networks (MFFNNBP) and data of different months, each month presents one season of the year.

Multilayer feed-forward with backpropagation neural networks (MFFNNBP) is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed forward process and then it performs the weights update to be back-propagated to the previous layers in order to recalculate the weights. Our proposed ANN architecture has three parts, one for producing solar energy prediction depending on previous real output measured along one year "2014" from three main solar panels located in Ain-Mousbah – Ramallah, Al-Oja – Jerico, and Al-Zababdeh- Jenin. These three energy collection points provide the power output within 5,10,30,60 minute's horizon of one month or one-year time horizon, then the data was processed according to the following process shown in figure 2.

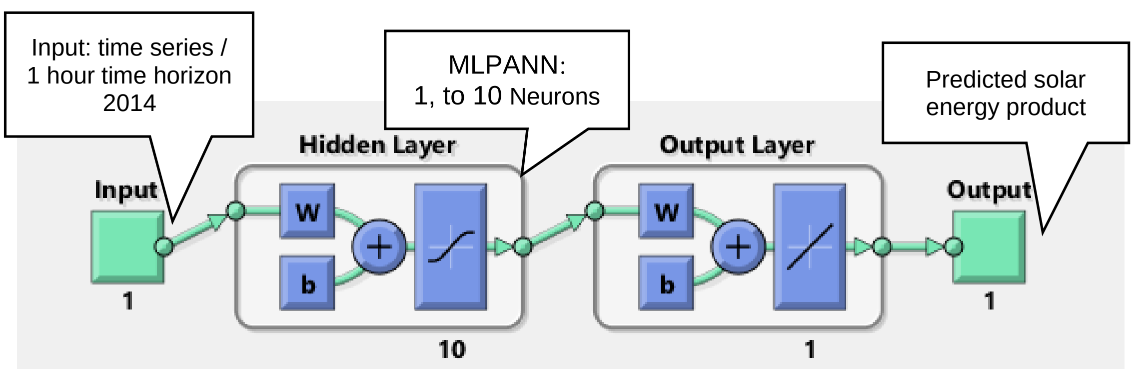

FIGURE 2: Proposed Solar Energy Prediction ANN.

The sigmoid activation function, f^1 is used [14]. In MLPNN, the output of a layer will be an input for the next layer passing from the input layer to the output layer; the equations used for this procedure are illustrated as follows:

$$output = f^2(\sum_{j=1}^{n} out_1 . w_{jk}) \qquad 5$$

Where the output of the first hidden layer *out₁*, which calculated using the following expression:

$$out_1 = f^1(\sum_{j=1}^{n} in_i . w_{ij}) \qquad 6$$

Where f^1 and f^2 are the activation functions for output layer and hidden layer, which calculated as in the following expressions:

$$f^1 = \frac{1}{1 + e^{-x}} \qquad 7$$

$$f^2 = x \qquad 8$$

Where, x = input vector. Depending on equations above, the weights are updated use as the following expression:

$$\Delta w_{jk}^n = -\mu \frac{dE(w_{jk}^n)}{d\, w_{jk}} \qquad 9$$

Where μ is the learning rate (normally between 0 and 1). The final output depends on all earlier layer's output, weights, and the algorithm of learning used [14]. Using data collected from previously mentioned solar panels, this data was preprocessed to reduce the noise from the input signal, this process increases the performance of the ANN and reduces the prediction error, using Matlab function called smooth function, then takes the signal and filters the noise by using average filter smooths data, then replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low-pass filtering with the response of the smoothing given by the next difference equation:

$$ys(i) = 12N + 1\big(y(i+N) + y(i+N-1) + ... + y(i-N)\big) \qquad 10$$

Where $y_s(i)$ is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of $y_s(i)$, and $2N+1$ is the span.

The backpropagation process calculates the gradient decent error between the desired and the predicted output considering the new weights each time, this gradient is almost always used in a simple stochastic gradient descent algorithm to find the weights that minimize the error. Different algorithms are used for training the feed forward with backpropagation neural networks, which train the NN and reduce the error values by adjusting and updating the weights and the biases of the connections that form the neural network, two kinds of training algorithms are available to slow convergence according to steepest descent methods with better generalization, and fast convergence according to newton's method, but these methods are complex because of the complex matrix calculations [19]. In our paper, we use one of the fast convergence algorithms, which is the Levenberg Marquardt Algorithm (LM) training algorithms [20], implemented by Matlab 7.1, and we use it in two steps; one is the training of time series using the time as input and the power generated by solar energy points as output, and the second step is to train the data produced by the factors that affect the energy production along the time.

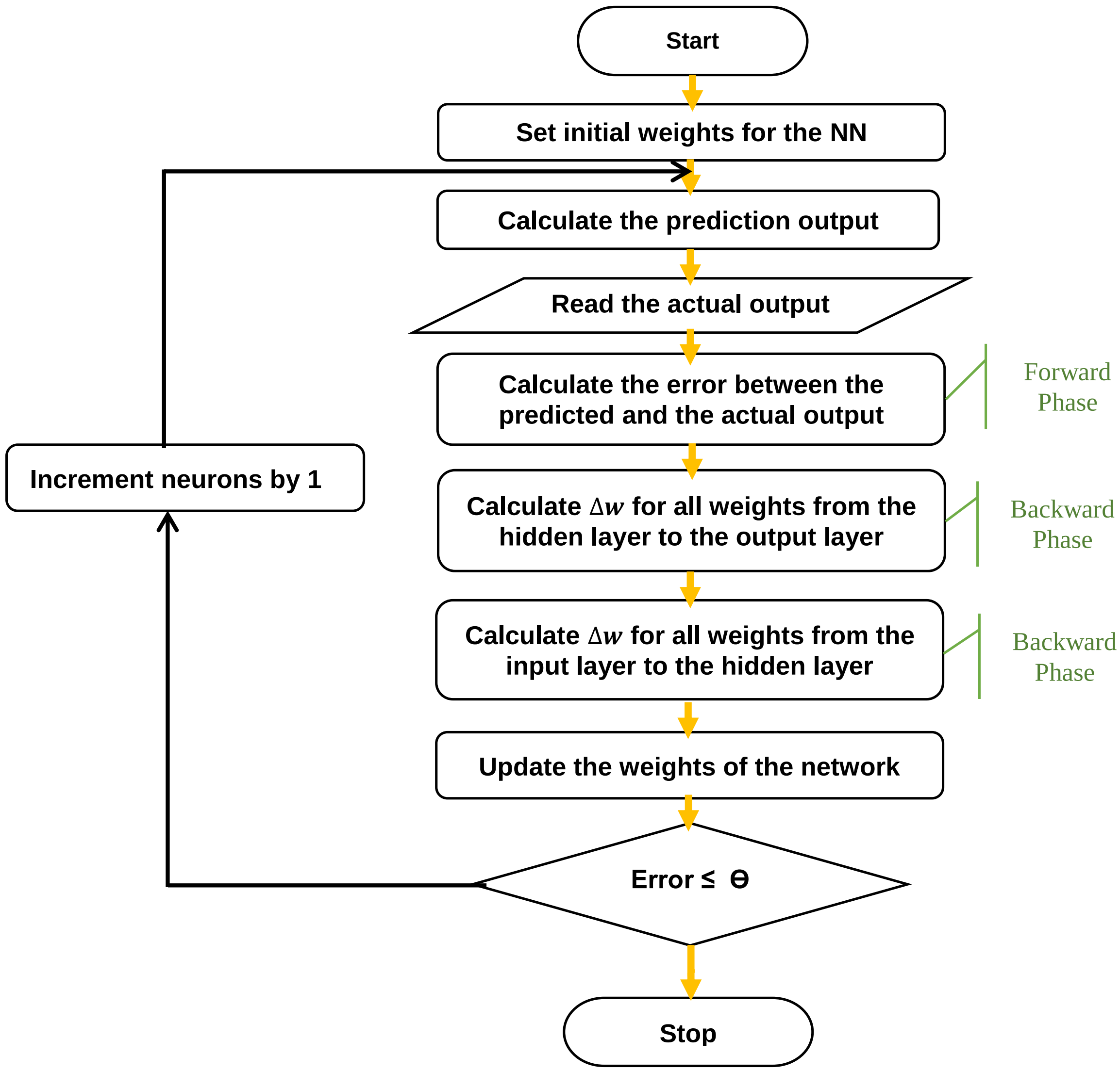

FIGURE 3: Flowchart of MFFNNBP Model.

4. RESULT AND DISCUSSION

Experiments have been performed to test the proposed prediction model. The model is simulated in MATLAB 7.1 under Windows 7 with processor i5. In this section, different examples are given to verify the procedure in the proposed model. Three different results are presented; One day, one month and one year. The results of the validity of the model in prediction samples of I/O data, compared with real results of the solar cell energy product of the last year in different areas in Palestine. The results are obtained in 5 executions; {# of neurons} the set of neurons used in each MFFNNBP. # of Epochs is the number of the execution cycle of the MFFNNBP. RMSEtest is the Root mean squared error of the training.

4.1 One Day Solar Energy Prediction

For one day prediction, we use data for each hour, which present the mean of all the read values in each 5 minutes. The day (1- Aug-2014) was selected with good climate conditions, like clear sky, long daytime, high solar irradiance, and medium humidity level, these conditions are highly effected the solar energy production. Applying the proposed model for one day of solar prediction produces the following results:

Solar prediction NN (# of neurons)	Epochs #	Train Data	Test Data	Validation Data	$RMSE_{test}$
2	11	70%	15%	15%	$7.6X10^{-5}$
4	29	70%	15%	15%	$3.16X10^{-5}$
6	19	70%	15%	15%	$1.64X10^{-5}$
8	22	70%	15%	15%	$3.3\ X10^{-6}$
10	19	70%	15%	15%	$1.8\ X10^{-6}$

TABLE 1: Results of Applying Proposed MFFNNBP in One-Day.

As seen from table 1, MFFNNBP plays a good role in solar prediction for one day, the real output for one day is a curve with some noise that are removed by using a smooth function as shown in figure 4. With one hidden layer of a small number of neurons, the proposed model predicts the future energy produced by the solar cell value in one day. This evaluated to find the RMSE of the MFFNNBP. Table 1 represents the test RMSE. In addition, figure 5 shows that the production process produces a fitting curve, with small values of RMSE.

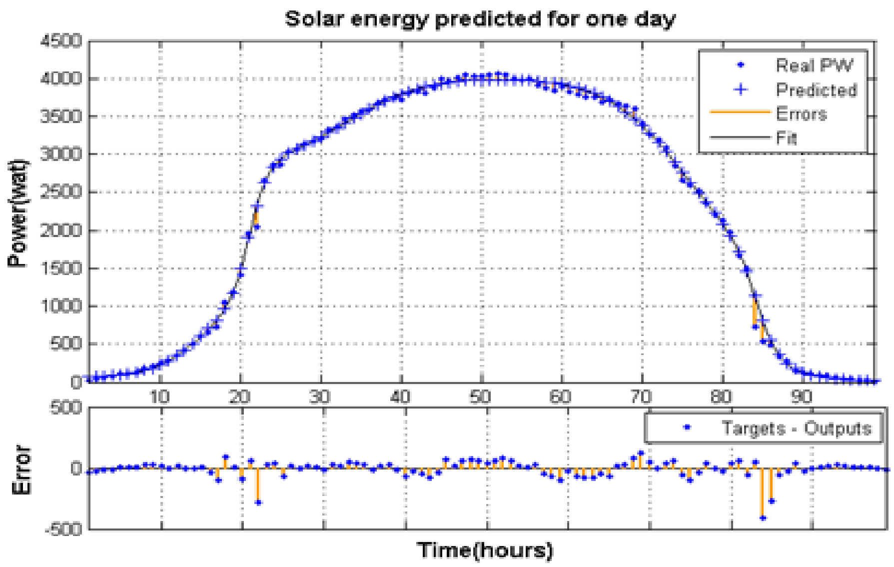

FIGURE 4: Power Generated for One Day.

4.2 One Month Prediction

To prove the process of predictions of the proposed models, we Applying the proposed MFFNNBP to predict energy that can produce in one month as the second part of the study, where July period of time was selected. Data was recorded for ALFA'A solar panel along the year 2014, and we built the training set for the July month record. The process was accomplished by taking the mean value of the generated power every 10 days with 10 readings per a day that can be illustrated in figure 5. Table 2 shows the results of applying proposed MFFNNBP for the training set which is formed of 30 examples, the results show that the best prediction result was achieved when hidden layer of 10 neurons was trained to give the following figures. According to the figure 6, the best prediction is achieved with 10 neurons in the hidden layer and 18 epoch. MFFNNBP produce small RMSE in monthly measured.

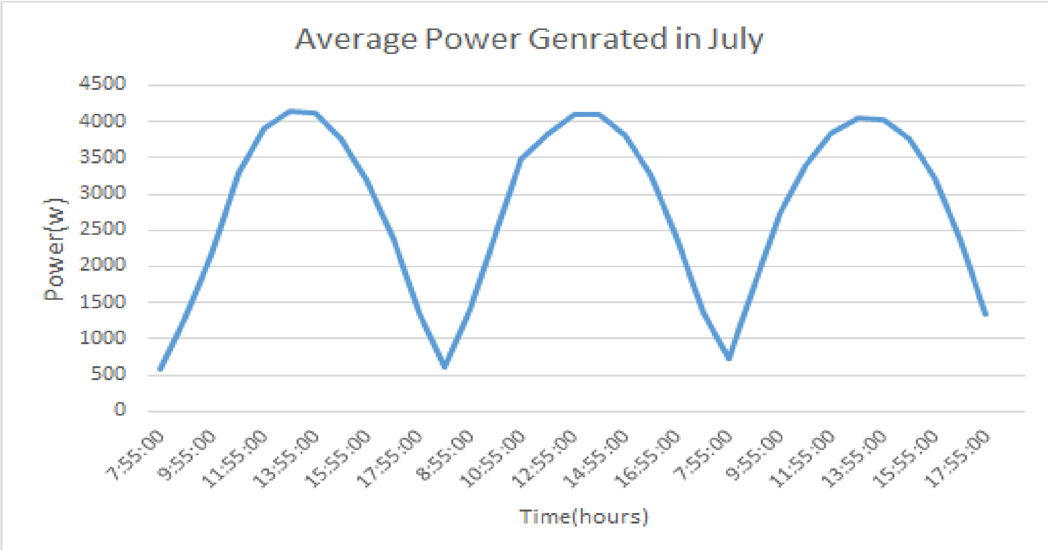

FIGURE 5: Mean Values Solar Energy Produced in July 2014.

Solar prediction NN (# of neurons)	Train	Test	Validate	Epochs #	$RMSE_{test}$
2	70%	15%	15%	8	0.091638
4	70%	15%	15%	9	0.072802
6	70%	15%	15%	11	0.000436
8	70%	15%	15%	18	0.000413
10	70%	15%	15%	18	0.000236

TABLE 2: Model Training Results for Energy Prediction at July (One-Month).

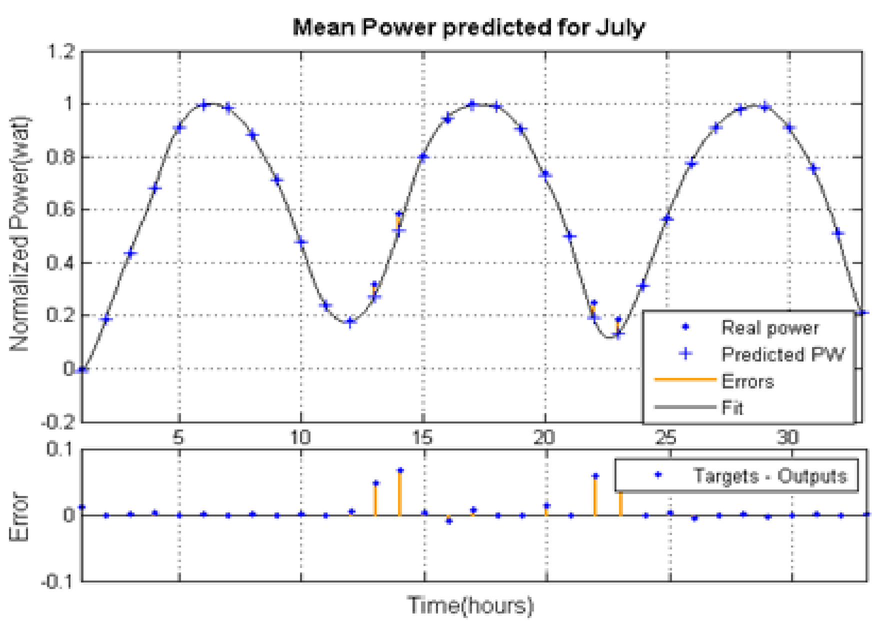

FIGURE 6: The Best Prediction Result of the Training Process for One-Month.

4.3 One Year Prediction

In order to get energy production along one year we need to deal with complex time series, figure 7 below shows the time series signal for one year [1-Jan-2014 to 1-Jan-2015], so we divided the year into four parts representing the four seasons of the year, dealing with each part as the mean value of the produced solar energy. As we see the high complexity of this signal, so we need to process it before we use it as target function to be predicted using the MFFNNBP model. This process started by; dividing the year into four parts, remove the night time where the energy produced goes to zero, reduce the large amount of data as Mean of one month = Mean [mean (1^{st} ,2^{nd} , 3^{rd} days) + mean (14 ,15 , 16 days) + mean (28 ,29 , 30 days), reduced the noise using smoothing function, normalization of the signal data, and applying the proposed model using several probabilities to get the best prediction results.

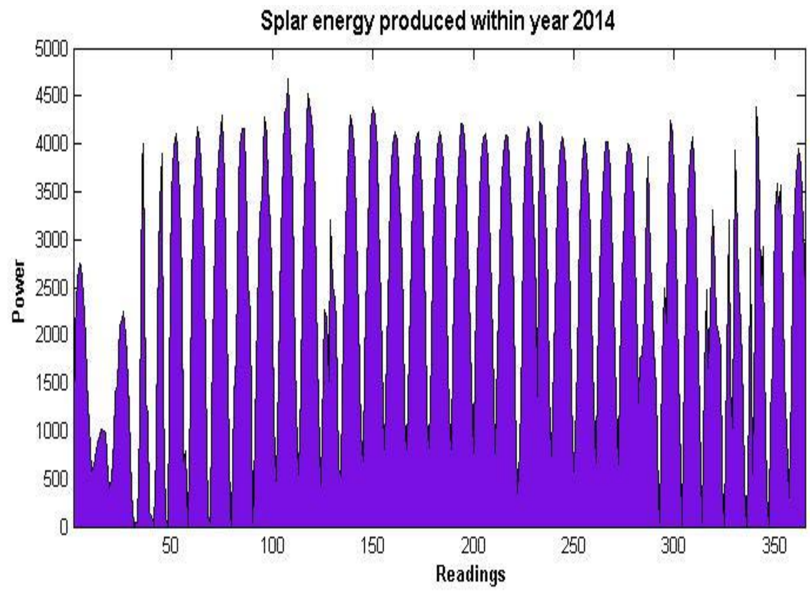

FIGURE 7: Energy Produced on One-Year.

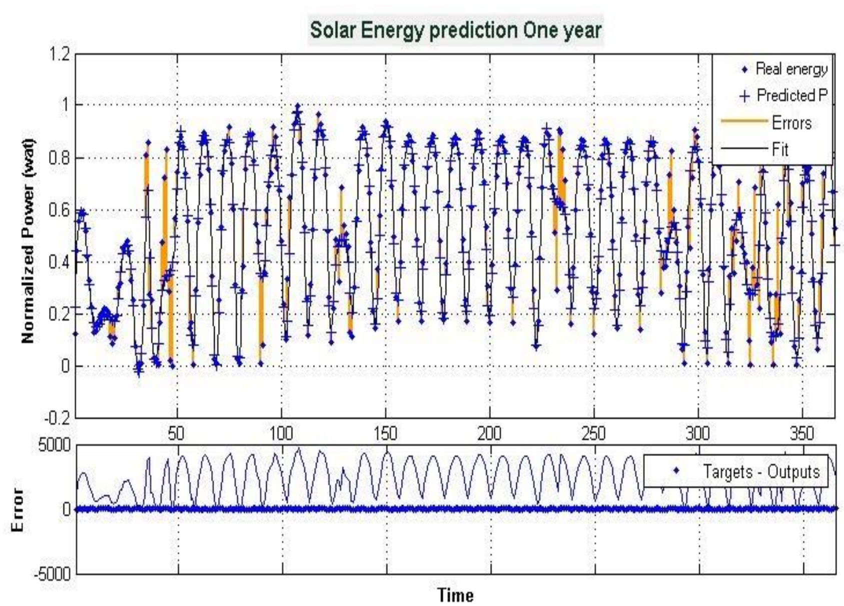

FIGURE 8: The Best Prediction Result of the Training Process for One-Year.

Figure 8 shows the best result for one-year prediction which was achieved when we applied the proposed model with 80 neurons in the hidden layer, and also shows the complexity of one-year time series solar energy prediction. As we see from figure 8 the error was at its minimum value with 90 neurons hidden layer is used [0.00564], which is the best error value, while when using more than 90 neurons the system will produce an overfitting problem. In all tables and approximation curves, we can observe the RMSE of the prediction, which clearly shows that the prediction is closest to the real value, regardless of the loss in the efficiency of the solar cells in energy production decreases by %5 in each year, all with a small number of epochs. The prediction process using the proposed model MFFNNBP was achieved using 80 neurons in the hidden layer, as shown in table 2 below:

Solar prediction NN(# of neurons)	**Train**	**Test**	**Validate**	**Epochs #**	**$RMSE_{test}$**
20	70%	15%	15%	7	0.070022
30	70%	15%	15%	8	0.067588
40	70%	15%	15%	9	0.064546
50	70%	15%	15%	22	0.039261
60	70%	15%	15%	11	0.035956
70	70%	15%	15%	11	0.01505
80	*70%*	*15%*	*15%*	*10*	*0.008242*
90	70%	15%	15%	12	0.00564
100	70%	15%	15%	12	0.008293

TABLE 3: Model Training Results for Energy Prediction for One-Year.

As we can see in the tables and figures, it is possible to observe the correlation values between real solar cell output power and power output obtained from the prediction using the proposed model MFFNNBP, that are measured in the same place. It is clear that we can consider the possibility of including other information as input to the model like, temperature, radiation, and humidity, and the time duration of the sunlight. This may perform better prediction of solar cell output power. Hence, the idea to predict more deeply the correlation between climatic parameters using NNs. The use of the MFFNNBP model for prediction of climatic variables becomes a viable solution for the knowledge of these values. The implementing of this model to solve a prediction problem is necessary to determine the optimum areas, where the solar cell panels can produce a more efficient power output. The obtained result, which use the MFFNNBP model for solar energy prediction, different attributes like training algorithm, training data, a region of study will change the values of the prediction result. This result obtained using real output data (previous data) as a measure of the prediction improvement, or prediction of the actual output using some input parameters. In the future work we will study the prediction process using the input data parameters that affect the power output of the solar cells like; temperature, radiation, and humidity, and the time duration of the sunlight. Furthermore, we will apply the model in two different types of solar cells; mono-crystalline and organic solar module, in the aim to determine the best type for our region.

5. CONCLUSION

In this paper, we used the energy produced data from solar panel located in different Places in Palestine for the year 2014, to train and test prediction technique that uses multilayer feed forward with backpropagation neural networks (MFFNNBP) trained using Levenberg-Marquardt algorithm, the model predicted the solar cells energy production for one day, one month and finally for the whole year with very high accuracy and low relatively number of processing units (neurons) to accomplish this task. The use of MFFNNBP for the prediction of solar cell energy output becomes a viable solution for the knowledge of these future values. In fact, the introducing of another meteorological system such as radiation, temperature, and sunshine hours and humidity may perform a significant improvement in prediction. From these results, we can predict the solar cell energy output for the next year, and we notice that August was the best month of the solar cell energy production, that is because of the clear sky, intermediate temperature, and long daytime which gives a long time of solar irradiation to produce energy. By looking at the figures obtained by the model you can perceive that this model predicts the future solar cell energy output in an accurate form.

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