Modeling Renewables Based Hybrid Power System with Desalination Plant Load Using Neural Networks

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ABSTRACT

Hybrid power system is seen as a viable alternative to the conventional systems. Estimating the potential of these hybrid power systems for a selected site is a major input required for making informed decisions. Often, estimation of the kWhr production is a very elaborate and tedious exercise due to lack of a reliable model for the same. This article proposed an Artificial Neural Network based model that can be used to easily estimate the total kWhr/year for a given combination of Solar PV, Wind generator and Battery. The variable load considered for the model is a desalination plant load. The data is modelled using Neural Network and validated. The proposed Neural Network model offers a reliable estimation on the total annual power generation for a given combination of Solar PV, Wind generator and battery capacity,

Keywords: Renewable energy; Hybrid power system; ANN, Desalination; RO; Solar; Wind; Battery, storage

INTRODUCTION – DESALINATION AND ENERGY

Renewable energy sources have emerged as a promising alternative towards building a sustainable and eco-friendly energy economy for the future. [1] Due to its intermittent nature, the reliability and availability is a major setback for these renewables. But hybrid power systems offer a feasible solution to increase the reliability and availability of renewable sources. These systems are deployed in remote places where main grid cannot be extended economically. Most of these places also have water scarcity and the desalination process itself is inherently energy intensive.

[2] [3] [4]. These desalination plant can also serve as an alternative medium of energy storage, act as a variable load. They produce water when the generation of power is excess.

The quick estimation of power generation that can be expected by these hybrid power systems is required to evaluate the desired configuration of the system. This article proposes modeling of the Solar PV-Wind system with battery and a variable desalination plant load to find out the total power generated for a year. This is modeled using Neural Network and the proposed model shall offer a good estimate of the total annual power generation figure with the capacities of Solar PV, Wind generator and battery as input.

MODELLING THE RENEWABLE ENERGY SYSTEMS

The availability of renewable energy sources differs from site to site and hence a details study is necessary with respect to various available resources is a prerequisite. We have chosen Solar Photo voltaic and Wind energy as sources for our work based on solar irradiance and wind speed data. The selected systems are required to be modelled for further analysis.

Solar Photovoltaic

Solar PV cells work on the basis of Photovoltaic effect that converts energy in the sunlight to electrical energy directly. A PV cell is made up of thin layers of semiconductor materials and the most common material used in Silicon. When light impinges on the Silicon layers, the energy is transferred to the electrons generating electrical charges. When these charges are conducted using metal external contacts, we obtain electrical energy in the form of direct current.

Modelling the Solar PV system is essentially finding the relationship between the solar irradiance and the corresponding power output from the PV cell. The same is given by Luque and Hegedus model of PV cell. [5] Table 1 gives the description of symbols used.

$$I = I_{SC}\left[1 - \exp\left(\frac{V - V_{\propto} + IR_s}{V_t}\right)\right] \tag{1}$$

$$I_{sc} = I_{sc}^{*}\frac{G}{G^{*}}\left[1 + \frac{dI_{sc}}{dT_c}(Tc - Tc^{*})\right] \tag{2}$$

$$Tc = Ta + C_t Geff \tag{3}$$

$$C_t = \frac{NOCT\ (^{o}c) - 20}{800W/m^2} \tag{4}$$

$$V_{\propto} = \left[V_{\propto}^{*} + \frac{dV_{\propto}}{dT_c}(T_c - T_c^{*})\right]\left[1 + \sigma_{\propto} 1n\left(\frac{Geff}{G_{\propto}}\right) 1n\left(\frac{Geff}{G^{*}}\right)\right] \tag{5}$$

$$Rs = \frac{V_{\propto}^{*} - V_M^{*} + V_t 1n\left(1 - \frac{I_M^{*}}{I_{sc}^{*}}\right)}{I_M^{*}} \tag{6}$$

$$P_v(t) = NpvVm(t)Im(t) \tag{7}$$

Equation (7) gives the estimated power output from the Solar PV cell. PV equipment is basically a static equipment without any moving parts. Hence the requirement for maintenance is very minimum. Also it has a long life of around 15 to 20 years. There is no emission of green-house gases and does not produce any noise during operation.

Table 1. Symbols used in Solar PV model equations

Symbol	Description
I_{sc}	is the short circuit current
V_{oc}	is the open circuit voltage
V_t	is the thermal voltage
R_s	is the series resistance
STC	is standard test conditions
I_{sc}^{*}	is the short circuit current of module at STC
V_{oc}^{*}	is the open circuit voltage of module at STC
G^{*}	is the Irradiance at STC
T_a	is the ambient temperature
T_c	is the operating temperature of module above ambient
T_c^{*}	is the temperature of module at STC
NOCT	is normal operating cell temperature
$\frac{dI_{sc}}{dT_c}$ and $\frac{dV_{oc}}{dT_c}$	are temperature coefficient of current and voltage
σ_{oc}	is the empirically adjusted parameter equal to -0.04
G_{oc}	is the empirically adjusted parameter taken as equal to the value of G^{*}
V_M^{*}	is the maximum voltage of module at STC
I_M^{*}	is the maximum current of module at STC.

Wind Energy

Wind energy is also an indirect form of solar energy. The difference of pressure in atmosphere is the basic source of wind energy. The high wind speed regions of the world has been more or less commercially exploited. Recently, small scale wind turbines are an essential part of standalone power systems that are distributed in nature rather than the conventionally centralized system. The power production of both Solar PV and Wind energy system can be largely improved by employing controls with maximum power point tracking and more efficient and effective energy storage systems.

The Wind energy is modeled using the below relation. Table 2 gives the description of symbols used.

$$P_w(t) = \begin{cases} 0 & (v < v_{in}) \\ a_1 v^2 + b_1 v + c_1 & (v_{in} \le v < v_1) \\ a_2 v^2 + b_2 v + c_2 & (v_1 \le v < v_2) \\ a_3 v^2 + b_3 v + c_3 & (v_2 \le v < v_{out}) \\ 0 & (v > v_{out}) \end{cases} \tag{8}$$

Table 2. Symbols used in Wind model equations

Symbol	Description
$P_W(t)$	is the hourly output power of wind generator at wind speed v
v	is wind speed at projected height
V_{in} and V_{out}	are cut-in and cut-off wind speed of the wind generator respectively

Reverse Osmosis (RO) Desalination Using Solar PV and Wind Energy

Many systems have been developed with reverse osmosis plants driven by Solar PV. [6] [7] Brackish water RO has minimum energy needs compared to other desalination process. Wind powered desalination plants are also being considered in many parts of the world. [8] [9] [10] The intermittent nature of Solar PV and Wind sources demand development of hybrid power sources with combination of these energy systems.[11][12]

The reverse osmosis (RO) desalination system typically has a motor as the major electrical load. This motor is used as drive for the high pressure pump. This pumps the feed water with the required amount of high pressure into the reverse osmosis membranes where the desalination actually takes place. From the RO membrane outlet, we obtain water with less salinity. For this work, we have chosen a RO plant of 1000 liters/hour capacity. The specific energy consumption for brackish water RO plant (i.e.) power required to produce 1000 liters of water is in the range of 1.5 - 2 kW. We have chosen 2 kW as the load of the RO plant on the higher side. The desalinated (sweet) water produced is stored in tanks typically of one day hold up capacity (around 24 KL). When the power produced by the Solar PV and wind is more the load required for RO plant, the RO plant operates at maximum capacity and produces sweet water. Further excess power keeps charging the battery. When the power produced reduces, the RO plant can still operate at reduced power producing less quantity of sweet water. Thus the RO plant acts as a variable load and can absorb any variation in renewable power generation. When the power generated is less than 0.5 kW, we cannot operate the RO plant and this power is utilized to charge the battery. The typical daily load profile expected for the desalination plant is given in the Figure 1.

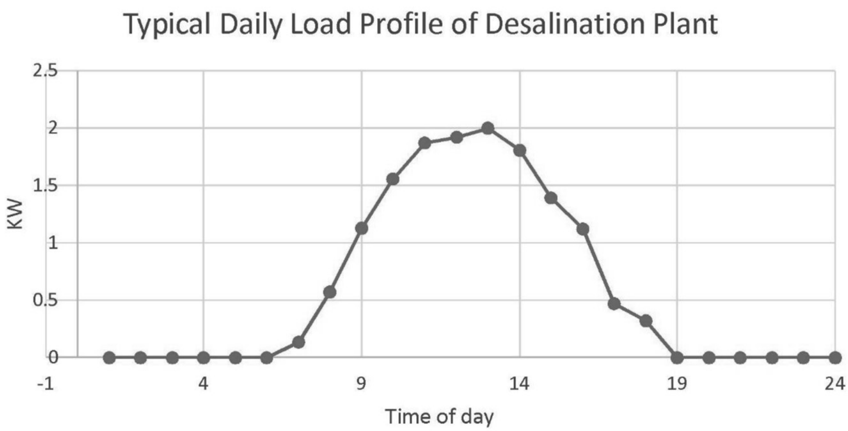

Figure 1. Typical daily load profile (expected) of the desalination plant

HYBRID SOLAR PV-WIND POWER SCHEME

Figure 2 shows schematic of the hybrid system with the desalination plant as load.

A brackish water RO desalination plant is connected as a load to the hybrid power system. This plant produces drinking water when the power available (both generated and stored put together) is sufficient to operate the plant. The water produced will increase up to its rated capacity, if the power produced is also more. Hence the load can handle variation in the power generation due to the renewable sources. The RO plant indirectly stores power produced in the form of product water thereby eliminating the need for having higher capacities of expensive batteries.

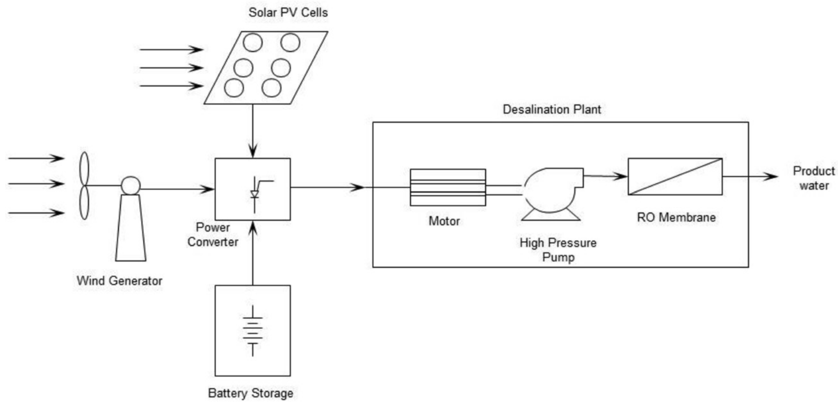

Figure 2. Schematic Diagram of a typical small Hybrid powered Desalination Plant

Analysis of Hybrid Power System with RO Plant

We have modeled the entire hybrid power system in MATLAB using the equations (1) to (8). The main objective of the model is to analyze the various combinations of Solar PV, Wind Generator and Battery capacities with a variable desalination load to obtain the total power generation.

Data

The hybrid power system design options are analyzed for the selected site, Kalpakkam. Kalpakkam is situated in South India and has the following latitude and longitude:

Latitude: 12°34′ North

Longitude: 80° 10′ East

The solar irradiation data are measured by using the 'Online Solar Radiation Meter' installed at the site and the wind data are extracted from the meteorological data available at IGCAR, Kalpakkam. Figure 3 shows the daily solar radiation profile of the selected site on a typical day during June for the 24 hours of the day.

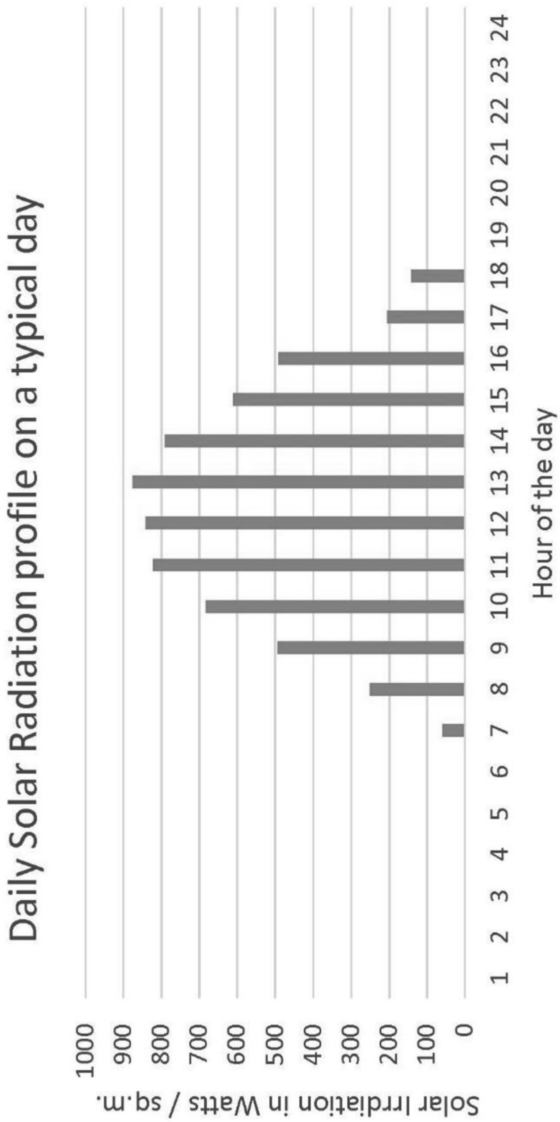

Figure 3. Daily solar radiation profile on a typical day

Figure 4 gives the average daily solar irradiation for all the twelve months of the year. We can see that the site receives an average of 5 kWh/m^2/day throughout the year.

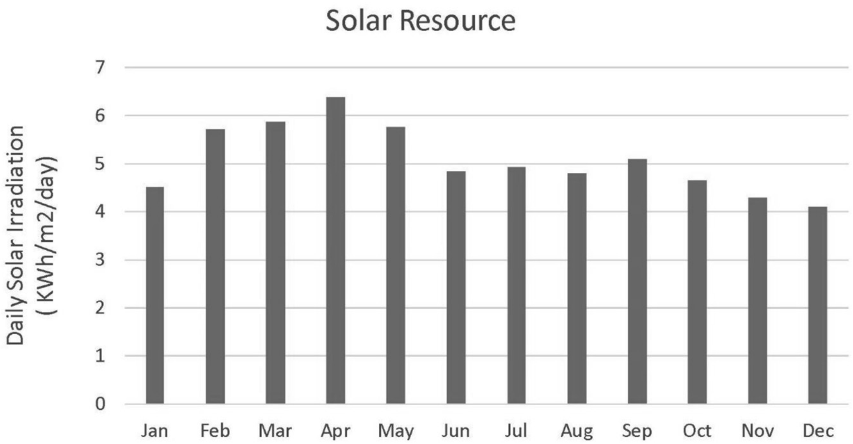

Figure 4. Solar resource throughout the year

Simulation Methodology

We have used the hourly solar irradiance data measured in kWh/m^2/day and wind speed data in m/s as inputs for simulation. The above data are used to calculate the power output available from PV and Wind sources using the models as per equations (1) - (8).

A Brackish water Reverse Osmosis (BWRO) plant with a capacity of 24 m^3/day is chosen as the load to be the system. This plant can operate at full load with 2 kW of power input and with reduced output up to a power input of 0.5 kW. Again, the power generated by renewables is calculated for every hour of the year. The power generated is utilized as per the following logic. When the power generated by the renewables is more than 2 kW, the plant will operate at full load producing rated output and excess power will be used to charge the battery. When the power generated is less than 2 kW and more than 0.5 kW, the plant will operate at lesser capacity. If the power generated is less than 0.5 kW, only batteries will keep charging and the plant will operate at lesser load using batteries until the battery is discharged to it maximum level beyond which the plant will shut down, and only batteries will keep charging.

The above simulation is carried out for various combinations of Solar PV capacities (1 kW to 10 kW), Wind generator capacities (1 kW to 10 kW) and battery capacities (0.5 kW to 2 kW).

Base Data for Modeling

The output of the simulation gives data on Total kWhr generation throughout the year for 400 combinations of Solar PV, Wind generator and Battery capacity for the ranges mentioned in Section 3.3. Table 3 lists the partial results of different configurations of hybrid power systems with BWRO plant load.

Figure 5 shows the plot of kWhr/year produced for various combinations of Solar PV, Wind and Battery capacities. We can observe that there is a clear increase in the power produced with BWRO plant. Also we can see that the increase in power production is more predominant when the capacities of Solar PV, Wind and Batteries are in lower ranges. This is because of effective utilization of power during low power periods. At higher ranges, the increase becomes more or less steady.

PV Capacity (in KW)	Wind Capacity (in KW)	Battery capacity (in KW)	KWHr/year produced with desal load
1	1	2	2557
1	2	0.5	3901
2	1	1.5	4773
2	1	0.5	5667
1	3	0.5	4928
1	7	1	7673
4	2	1	7167
1	9	2	8652
3	4	0.5	7862
2	7	2	8716
5	2	1	7520
4	3	0.5	7774
3	5	2	8396
2	8	2	9153
4	4	2	8302
4	5	2	8799
2	10	2	9918
10	1	0.5	8660
5	6	0.5	9483
7	5	1	9421
4	9	1.5	10360
8	6	2	9921
8	7	0.5	10283
8	8	1	10609
10	8	1.5	10759
8	10	0.5	11200
10	10	2	11332

Table 3. Partial list of different configurations of hybrid power systems and kWhr/year generated with BWRO plant load

Proposed Neural Network Model

A Neural Network model is proposed to estimate the total kWhr produced for the year for a given set of Solar PV capacity, Wind generator capacity and storage battery capacity (in kW). The input lay is composed of three nodes in inputs which are:

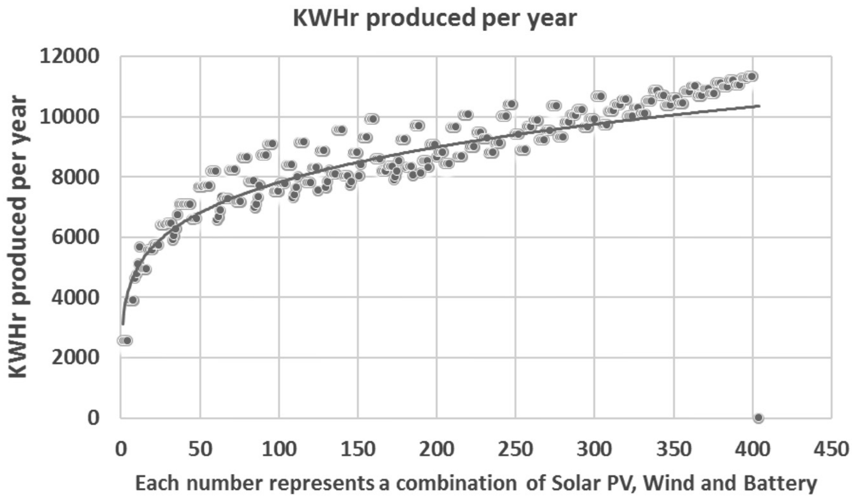

Figure 5. Plot showing increase in kWhr/year produced with BWRO plant as load

i) Solar PV capacity
ii) Wind generator capacity
iii) Storage battery capacity

The hidden layer is composed of four nodes whose activation function is the hyperbolic tangent sigmoid transfer function. The output layer is composed of one node and this represents the required output (i.e.) the estimated total kWhr produced for the year for a given set of capacities as input. The neural network architecture is shown in Figure 6.

We have got 400 data sets for Solar PV, Wind generator & Storage battery capacities as input and the total kWhr produced for the year as output. The data set is used for training of the chosen neural network. The weight values are adjusted using this data set during training according to the error calculated. The training was carried out using Levenberg-Marquardt algorithm. The entire procedure was done using MATLAB/Simulink. The neural network models the data into the relationship as given in equation 9.

$$\text{kWhr/year produced} = b2 + LW * \tanh [(b1 + IW * (\text{Inputs} - \text{Solar PV kW}, \text{Wind kW}, \text{Batt. kW})] \quad (9)$$

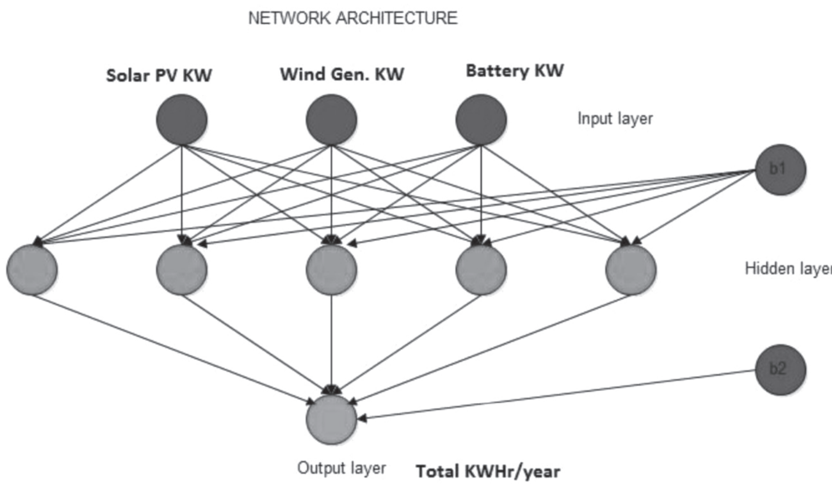

Figure 6. Proposed neural network architecture for estimation of total kWhr produced per year

where IW is the input weight matrix, b1 is the bias for hidden layer, LW is the hidden layer weight matrix, b2 is the bias for the output layer. The values of weight matrices and biases are given in Table 4. Using equation 8, we can instantly obtain the estimated total kWhr produced in a year for a given capacity of Solar PV, Wind generator and Battery for the selected site.

Table 4. Values of Weight matrices and biases

IW	b1	LW	b2
[-2.2208 -0.096177 -0.018034; -0.18876 0.31461 -0.00066758; -1.8081 0.49754 2.239; 6.3759 0.5142 -0.010182; 1.7715 1.2849 -0.043931]	[-1.0518; -0.44379; 0.080092; 4.8492; 2.9711]	[-0.16632 -1.3172 -0.00112 0.16754 0.27026]	[-0.58362]

Verification

The verification of the fitted neural network model was carried out by using a total of 60 sets of input/output data. The input data were used in the proposed model as per eqn. 9 and the output was generated from the model. The output from the model is compared with the targeted set of output data. This comparison is carried out using the regression analysis which finds out the correlation between the model output data and the expected response from the system. The regression value of 1 is ideal which shows a perfect matching of both the data sets and hence an accurate model.

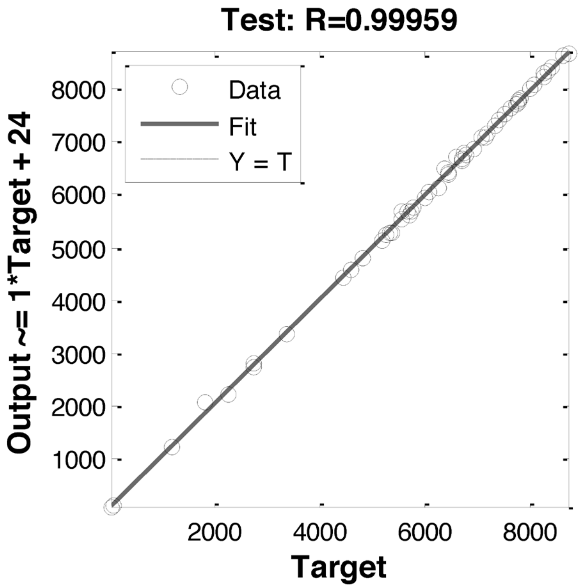

Figure 7. Regression plots of neural network model for verification

Figure 7 shows the model performance during verification. We have obtained a regression value of 0.9995. This value indicates a very high level of correlation between the predicted value by the model and the actual value. This shows that the fitted model is accurate and the model is acceptable.

Validation

We have chosen 60 sets of input/output data for validation of the model. These data were presented as inputs to the neural network model to calculate the output. The predicted value of output is compared with the actual value. The correctness of modeling algorithm was checked by comparing the output generated by the model as per eqn. 9 and the actual output data (i.e.) target. We have used regression analysis to check the correctness of the model. The regression values are close the one which indicates a very high correlation between the input/output data and the model data. We have obtained the regression (R) of 0.9994 which shows that the model is accurate. Thus the model algorithm is validated.

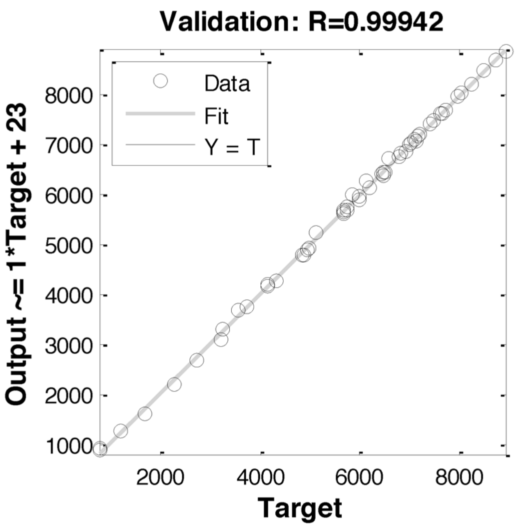

Figure 8. Regression plots of neural network model for validation datasets

CONCLUSION

In this article, modelling of renewable energy based desalination systems with Solar PV and Wind turbines was presented. The above configuration was subjected to detailed simulation to analyze the performance of the system under constant load of 2 kW and a BWRO plant load of 2 kW maximum. A neural network model is proposed for the above system with Solar PV, Wind generator and battery capacities as inputs and total kWhr production per year as the output. The chosen architecture was trained to obtain the required performance. The NN model fitted gives very high regression value close to one indicating the accuracy of the NN model. With the model we will be able to easily estimate the total kWhr produced in a given year for a given capacity of Solar PV, Wind generator and Battery capacity.

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