DEVELOPMENT OF A SOLAR ENERGY TRACKING MECHANISM WITH ARTIFICIAL NEURAL NETWORK ENHANCEMENT

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ABSTRACT

A solar tracker is a generic term used to describe a device that orients solar panel towards the sun. Solar trackers are employed to maximise the quantity of energy generated from a fixed amount of installed photovoltaic (PV) cells. This paper presents a solar tracking system enhanced with an artificial neural network to maximise power output. The system consists of a solar panel always facing the direction of the sun with the aid of a solar tracker mechanism controlled by a servo-motor and Light Dependent Resistor. The collected solar power data was used to train a neural network for irradiance, power and tilt prediction. The neural enhanced solar tracking system was able to predict the output power with satisfactory accuracy.

Key word: Solar power, tracking mechanism, servo-motor, photovoltaic panel, renewable energy, neural network.

I. INTRODUCTION

A key problem the world is facing currently is the exhaustion of fossil energy. This is because the demand for electrical energy nowadays is very high due to the increasingly rapid development. So the non-renewable energy like fuel and coal may run out soon if this energy demand continues. Because of these matters, Worldwide scientists now are busy searching for renewable energy like solar, hydro and wind. These energies are the best solutions for the problems that the world is facing nowadays (Stephenson, 2007).

There is much preference for solar power as a source of electrical energy owing to its enabling environmental sustainability. It is flexible for different applications. To use solar power for electricity, the photovoltaic (PV) cell is used. However, the energy trapped by a photovoltaic (PV) cell can be enhanced with the aid of a solar tracking mechanism (Nnadi, et al., 2014; Akorede, et al., 2010). The solar tracker system follows the solar radiation to more power quantity. According to (Nnadi, et al., 2014), who used a mechanical maximum power point tracker, a gain of 5.77% is achievable in a solar tracker incorporated solar system than a fixed solar panel system. Thus panel cost is minimised for large scale deployment. This system eliminates the need for operators to manually vary the tilt and direction of the panel.

Description of types of solar tracking systems such as single-axis and dual-axis types are presented in (Frankin, et al., 2004, Gil, et al., 2009, Solar Navigator, 2013). Figure 1 shows the schematic diagram of a passive solar tracker. Figure 2 shows the solar panel view when a tracking system is used.
Therefore, this research intends to develop a solar tracking mechanism that tracks the sun during the daytime and thus increase outputted power using the Light Dependent Resistors (LDR). Furthermore, the data collected by the solar power system will be used in training an artificial neural network system.

Chowdhury, Khandakar, Hossain & Abouhasera (2019) developed “a standalone low-cost but high-precision dual-axis closed-loop sun-tracking system using the sun position algorithm was implemented in an 8-bit microcontroller platform. "The Astronomical Almanac’s (AA) algorithm was used for its simplicity, reliability, and fast computation capability of the solar position”. “Results revealed that incorporation of the sun position algorithm into a solar tracking system helps in outperforming the fixed system and optical tracking system by 13.9% and 2.1%, respectively”.

Abdollahpour, Golzarian, Rohani & Zarchi (2018) proposed “a dual-axial tracker that works based on processing images of a bar shadow. The system was composed of a shadow casting object, a webcam, electronic circuits, computer controls, and stepper motors”. “The webcam was used to capture images of the shadow. The
study results showed that the tracker system followed the sun with an accuracy of about ±2° and maintained the panel perpendicular to the irradiation direction. This system works independent of its initial settings and can be used in any geographical regions. It managed to hold the panel perpendicular to irradiation to receive the maximum solar energy and thus generate the highest power output.

II. MATERIALS AND METHOD

Figure 3 shows the block diagram of the entire system. It includes a servomotor, a microcontroller, a laptop with LabView application installed and LDR. The LabView program will also include monitoring and display of light intensity output from the LDR.

Figure 3: Block diagram for solar tracker using servo motor (Krishna & Sinha, 2013)

Neural Network Modelling of Solar Power Tracking system

Continuous solar power measurement is time-consuming. This has motivated the deployment of prediction technique to solar observations (Nadia, Isa & Desa, 2020; Robles Algarín, Sevilla Hernández & Restrepo Leal, 2018).

Artificial Neural Network (ANN) seeks to mimic the Biological Neural Network (BNN). Whereas a BNN is made up of biological neurons, physically connected in the nervous system, the ANN consists of artificial neurons functionally interconnected, creating a programme-like structure with the capacity to mimic the behaviour and processes of biological neurons in terms of organisation and learning. Thus, ANN possesses some features of the brain like massive parallelism, adaptivity, ability to learn and generalize, distributed representation and computation. Other features include the ability to process contextual information, low energy consumption, and fault tolerance. Owing to the rapid adaption required of cognitive radio, ANN has been used for prediction purposes.

Figure 4: ANN-based time series prediction

Connection to each neuron to another neuron for times series prediction is shown in Figure 4. In NN back propagation a set of inputs \( \left( x_1, x_2, \cdots, x_i \right) \) are correlated to a set of outputs \( \left( y_1, y_2, \cdots, y_f \right) \). The input is
iteratively multiplied by the weight. Weighted inputs to each upper layer unit are summed up as shown in Eqn. (1):

\[
y_i = f \left( w_{o} \{ w_{h}x_i + \phi_{h} \} + \phi_{o} \right)
\]

where \( w_{o} \) = output weight, \( w_{h} \) = hidden layer, \( \phi_{o} \) = output bias, \( \phi_{h} \) = hidden layer bias and \( f (\cdot) \) = sigmoid activation function. However, activation functions could be threshold, piece-wise linear and Gaussian.

In the implementation of the neural network, the objective function is to minimize the error function such as the Sum of Square Error (SSE) expressed in Eqn. (2):

\[
E = 0.5 \sum_{i=1}^{N} (t_i - y_i)^T (t_i - y_i)
\]

where \( t_i \) = target output for pattern \( i \)

The gradient descent is used to adjust the inter-neuron weights. If the fan-in weight to a neuron is represented by weight \( w \), then the update in the \( k^{th} \) epoch is defined by Eqn. (3):

\[
\Delta w_k = -\eta \nabla E (w) |_{w = w(t)} + \alpha \Delta w_{k-1}
\]

where \( \eta \) = learning rate, which controls the step size of each iteration, \( \alpha \) = momentum factor.

The gradient descent will be modified with the Levenberg-Marquardt algorithm to quicken the convergence of the neural network algorithm.

The flow chart of the artificial neural network-based solar power prediction process is shown in Figure 5.

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**Figure 5:** Flow chart of the process of artificial neural network-based solar power prediction

This work would be limited to developing a solar energy tracking mechanism for the Federal Polytechnic, Offa. Offa is a town located in Kwara State, North Central, Nigeria, with coordinates: longitudes 8° 30’ 05” N and latitude 8° 15’ 55” E. (Mustapha 2009).
Experiment setup

- System configuration and fitness function
The ANN prediction models used in this research are implemented in MATLAB R2018a on a computer with the following configuration: Intel Core i5, CPU 2.88 GHz, RAM 8 GB, 64-bit operating system. All experiments are conducted on the specified machine. The number of hidden neurons used is 10 and the number of delays is 2. The number of the output layer is 1.

- Hardware Configuration
The specification of the photovoltaic cell and servo motor used are shown in Tables 1 and 2.

Table 1: Specification of the solar panel

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-circuit current ($I_{sc}$)</td>
<td>4 A</td>
</tr>
<tr>
<td>Open circuit voltage ($V_{oc}$)</td>
<td>21.7 V</td>
</tr>
<tr>
<td>Voltage at $P_{max}$ ($V_{pmax}$)</td>
<td>17.5 V</td>
</tr>
<tr>
<td>Current at $P_{max}$ ($I_{pmax}$)</td>
<td>3.71 A</td>
</tr>
<tr>
<td>Temperature coefficient of voltage ($T_{cv}$)</td>
<td>0.0802 $^\circ$C</td>
</tr>
<tr>
<td>Temperature coefficient of current ($T_{cl}$)</td>
<td>0.0024 $^\circ$C</td>
</tr>
<tr>
<td>Maximum voltage ($V_{max}$)</td>
<td>22.35 V</td>
</tr>
<tr>
<td>Minimum voltage ($V_{min}$)</td>
<td>18.44 V</td>
</tr>
</tbody>
</table>

Table 2: Specification of the servo motor

<table>
<thead>
<tr>
<th>Type</th>
<th>Robotis RX-64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size [mm $\times$ mm $\times$ mm]</td>
<td>61.1 $\times$ 40.2 $\times$ 41</td>
</tr>
<tr>
<td>Torque [Kgcm]</td>
<td>64 (18V)</td>
</tr>
<tr>
<td>Speed [sec / 60deg]</td>
<td>0.162</td>
</tr>
<tr>
<td>Weight [g]</td>
<td>116</td>
</tr>
<tr>
<td>Voltage [V]</td>
<td>18</td>
</tr>
<tr>
<td>Operation current [A]</td>
<td>1.2 (Max)</td>
</tr>
<tr>
<td>Operation angle range [deg]</td>
<td>300/ Endless turn</td>
</tr>
<tr>
<td>Communication speed [bps]</td>
<td>1Mbps</td>
</tr>
<tr>
<td>Manufacturer</td>
<td>Robotis</td>
</tr>
</tbody>
</table>

III. RESULTS AND DISCUSSION

Before applying the neural network in the training of the solar power data, the data sample sizes for training, testing and validation were investigated. The most accurate sample partition of 70-15-15 was used in predicting the smoothen data and the response and error histogram are shown in Figures 6 and 17 respectively.

Figure 6: Plot average ANN response to the smoothen solar power output
The MSE obtained was 0.0025. From the error histogram, it will be observed that the errors are concentrated around -0.08072 to 0.06147.

Figure 7: Error histogram from the ANN-based prediction

Figure 8: Solar irradiance plot neural-solar tracking vs. fixed system

Figure 9: Solar power under cloudy condition plot neural-solar tracking vs. fixed
The results obtained in the implementation of the neural network enhanced tracking system for 48 hours in partially cloudy conditions is shown in Figure 9. In the power curve, fluctuations can be observed due to the variations obtained with the voltage sensor. The increase in the battery voltage curve reflects that the battery is being properly charged with the use of the two controllers; highlighting the advantage of the neural enhanced system that presents minimal oscillations. The tilt predicted values are shown in Figure 10.

IV. CONCLUSION

This paper proved that an artificial neural network can be utilized to design and implement solar tracking systems. The data sample partition of 70-15-15 gave the most accurate prediction.

ACKNOWLEDGEMENT

This work was funded by Tertiary Education Trust Fund (TETFUND), Nigeria under the Institution Based Research (IBR) Grant Batch 6 RP disbursement. We also acknowledge the Research and Innovation Unit of the Federal Polytechnic Offa, Kwara State, Nigeria.

V. REFERENCES


