**An FPGA-in-the-Loop Simulation of a Neural Network-based Optimization of Greenhouse Supplemental Illumination**

Alejandro H. Espera, Jr, Wen-Yaw Chung, and Rosula S.J. Reyes

**Abstract**—Greenhouse crops depend on sufficient amount of light to achieve photosynthetic efficiency resulting to their full development and growth. So supplemental illumination is needed when insufficient light has accumulated throughout the day to help achieve the required Daily Light Integral (DLI) for the crops. The lighting schedule and the energy usage are the top concerns of the crop growers in their supplemental lighting operations. In this study, an FPGA-based system was developed to manage the operations of the supplemental illumination, giving the crop growers the option to set the lighting schedule and the target DLI supplementation by selecting the desired energy saving mode. The designed system was able to control the lighting operation within the lighting schedule set by the user. Its capability of saving energy is dependent on the daytime lighting. In testing, the system was able to save energy when high to average energy saving mode selected for low to average target DLI, but not when selecting low energy saving mode for high target DLI supplementation. The system was capable of achieving the target DLI value based on the chosen target DLI requirement for the crops.

**Keywords**—DLI, FPGA, Greenhouse Lighting, NN

**I. INTRODUCTION**

The increase of plant’s biomass is generally referred to as growth in plant science. Specifically, plant’s growth is associated with the production of new leaves, stems, fruit and other physiological development. Monitoring each stage of plant’s growth is critical for maximizing the production especially in the crop production industry. A good balance of vegetative and generative growth must be achieved for a sustainable production [1]. This prompts the growers to manage the development of the crops by controlling parameters such as the temperature and humidity to aid photosynthesis under the given light conditions [2].

For photosynthesis to initiate, the plants need visible light with wavelengths between 400 and 700 nanometer range. But in this specific range, plants tend to make more use of some wavelengths than others. According to Salisbury and Ross, all plants exhibit use of light that peaks in the proximity of 650 nanometer (red) region and a smaller peak in the proximity of 450 nanometer (blue) region. Thus, only about 22% of the light is absorbed in that particular range of wavelength which makes plants relatively inefficient at absorbing light [1]. Wilson in 1992 stated that plants’ efficiency depends on specific photosynthetic efficiency and the efficiency of light interception [3].

Greenhouse cultivation industry has risen throughout the years and has become popular for growing commercial crops efficiently. By January 2015, the estimated global area that cultivates greenhouse vegetables have reached to 414,127 hectares of land (based on official government statistics, published research reports and extensive research for other specific data). About 1,825 known greenhouse vegetable growers in 95 countries in the world own about 15,340 hectares of greenhouse vegetable production area (not including government statistics on individual grower’s information) [5].

Greenhouse production is not an easy task. It requires proper planning and management. Several important factors must be considered such as site selection, structural design, climate control, light management, choice of plant species, water requirements and irrigation management, soil fertility and plant nutrition, pest management, harvest and post-harvest management, preventive environmental strategies, product safety, product labelling and certification, and energy use [4].

Among the important factors in operating a greenhouse farm, one of the critical consideration is how to manage the light with the goal to supplement the right amount to the crops. This may directly affect the quality and quantity of the crop product, which likewise translates into the amount of energy consumed by the lighting system. Researchers have put their interest and have been conducting studies in the area of precision farming and horticulture, focusing on manipulating the light supplementation for the plants using artificial lights [5].

An efficient lamp must translate as much of the electrical energy into energy useful for plants, the photosynthetically active radiation (PAR) energy. LED light spectrum is wider compared to traditional projection lamps which focuses more on the yellow-to-red spectrum of light while LEDs cover wavelengths from 400 to 700 nanometers of light with concentrated power on the blue and red portions of the
spectrum, which is the most required light spectrum for plant growth, as shown in the comparison in Fig. 1 [6].

![Light spectrum efficiency comparison](image)

**II. PROPOSED WORK**

The Daily Light Integral (DLI) is the measure of light’s photosynthetically active radiation (PAR) received daily by plants. DLI is achieved by averaging the PAR values (expressed in µmol/s) for the entire day. The greenhouse production industry believes that DLI can have a substantial effect on the quality and quantity of their crop yield [7]. So commercial growers need to consider how they can manage their lighting schedule to accommodate the DLI needed despite of the erratic behavior of natural lighting during daytime. In turn, they also need to address energy usage for the lighting system used as supplemental illumination for their crops. An automated management system is necessary to deal with the existing concerns of the greenhouse growers.

Fig. 2 shows the system framework for this study. The Field Programmable Gate Array (FPGA) prototype comprises of three main components: input management, PAR-based light supplementation Artificial Neural Network (ANN) model, and the lighting control. The input management receives and prepares the input data set by the user (Energy Saving Mode and Lighting Schedule) and the PAR data from the PAR sensor. The optimization is done in the PAR-based light supplementation ANN model. Then the lighting control component manages the lighting schedule of the output lighting system.

![System framework](image)

The system was designed to automate the switching on and off operation of lighting system within the range of time schedule initially set by the user. The main goal was to achieve the target DLI supplementation for the crops associated with the energy saving mode initially set by the user (as shown in Table I), and results to minimization of energy usage.

**III. METHOD AND DESIGN**

An artificial neural network (ANN) is generally based on the neural structure of the brain and is represented as electronic network of "neurons". A neuron is basically an element which accumulates inputs from previous neurons with different strengths. What it does more is that it compares the accumulated inputs with one predefined value unique to every neuron. This value is called bias. Its process is to record inputs and outputs for each neuron one at a time, and "learn" by comparing their output with the known actual record. The errors from the initial output of the first record is fed back into the network, and used to modify the networks algorithm the second time around, and this is repeated for multiple iterations. The multilayer feedforward network in Fig. 3 is one of the most commonly used ANN topology. It consists of three layers: input, hidden and output [9].

![Multilayer feedforward neural network](image)

A feedforward with backpropagation neural network model was developed in the Mathworks Matlab Neural Network Toolbox [10] using the average DLI supplementation for various greenhouse crops data coming from Ball Redbook for reference (as summarized in Table I) so as to maintain generalized and non-crop-specific decisions in the operations [8]. Table II shows the summary of the neural network design and Fig. 4 shows the neural network structure.

The three input neurons represent the input data: target DLI/energy saving mode, light-on schedule and PAR reading. The output neuron correspond to the optimized number of light operating hours starting from the light-on time until time 0:00 (12:00 AM) of the lighting schedule.

The input data needed to be normalized as it passed through the neural model with scaled values between -1 to 1 for the neural network to process. The data were prepared for training by randomly dividing it into three parts: 70% for training, 15% for validation and 15% for testing. The error for training and validation must converge to minimum, which then was evaluated using the testing data. The hidden layer directly received the data from the three neurons that represented the input data. The hidden layer processed the data using two neurons and transferred it to the output layer.

**TABLE I  AVERAGE DAILY PAR SUPPLEMENTATION**

<table>
<thead>
<tr>
<th>Target DLI</th>
<th>Crop Quality</th>
<th>Average Daily PAR Supplementation[µmol/s]</th>
<th>Energy Saving Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Acceptable</td>
<td>70-140</td>
<td>High</td>
</tr>
<tr>
<td>Medium</td>
<td>Good</td>
<td>140-230</td>
<td>Average</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>230-300</td>
<td>Low</td>
</tr>
</tbody>
</table>

![Image]
using hyperbolic tangent sigmoid transfer function. The output layer with one neuron processed the data then transfers it to the output block via pure linear transfer function. This process flow is represented in Fig. 4.

### TABLE II
**NEURAL NETWORK DESIGN SUMMARY**

<table>
<thead>
<tr>
<th>Design Specification</th>
<th>PAR-Based Supplementation Neural Network Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN Type</td>
<td>Feedforward with Back Propagation</td>
</tr>
<tr>
<td>Sampling</td>
<td>1 hour</td>
</tr>
<tr>
<td>Transfer Functions</td>
<td>Hyperbolic Tangent Sigmoid / Pure Linear</td>
</tr>
<tr>
<td>Normalization</td>
<td>-1, 1</td>
</tr>
<tr>
<td>Training Function</td>
<td>Levenberg-Marquardt</td>
</tr>
<tr>
<td>Training Data</td>
<td>70 %</td>
</tr>
<tr>
<td>Validation Data</td>
<td>15 %</td>
</tr>
<tr>
<td>Testing Data</td>
<td>15 %</td>
</tr>
<tr>
<td>Input Neurons</td>
<td>3</td>
</tr>
<tr>
<td>Hidden Neurons</td>
<td>2</td>
</tr>
<tr>
<td>Output Neurons</td>
<td>1</td>
</tr>
</tbody>
</table>

The neural network training performance ceased to increase after epoch 14 and stopped during epoch 20. Best validation was achieved with Mean Square Error of 0.33347 at epoch 14 after 6 validation checks as shown in Fig. 5. The neural network training regression results are shown in fig. 6 with quite consistent R values in training, validation and testing data and an overall R value of 0.99236.

The Simulink model shown in Fig. 7, block by block, is based on the process flow of the neural network structure in Fig. 4. The input port 4 and output ports 2, 3 and 4 on the lower part are transport wires transferring data from previous to next subsystem. This is the center model and this is termed as the NN base model subsystem.

As shown in Fig. 8, the input management subsystem comprises of the Daily Light Integral calculator component and transport wires for the other input data: target DLI/energy saving mode, light-on and light-off schedule. The convert blocks convert the input data to fixed-point data type which was necessary for the neural network model process. The DLI calculator computes for the real-time DLI value as it accepts the actual hourly PAR reading from the sensor and sends the DLI value to the ANN model subsystem via output port 3, then resets to zero every after the end of the day.
Fig. 8 Input management subsystem

The lighting control subsystem as shown in Fig. 9 is the subsystem that receives the data from the ANN model subsystem. The lighting control subsystem consists of two main components, the scheduler and the corrector. The main function of scheduler is to control the turning on and off of lights within the specified lighting schedule. The scheduler accepts the lighting schedule which is set by the user and the data from the corrector. The corrector receives the light-on schedule and the output data from the neural network model via the input port 1 in this subsystem. Since the neural network output is the optimized number of hours that it takes to keep the lights on, the corrector continually adjusts the specified lighting schedule to the optimized schedule to meet the target DLI considering the opted energy saving mode. The output of the scheduler is either 1 or 0, denoting on and off respectively.

Fig. 9 Lighting control subsystem

The complete system model was designed in Mathworks Simulink using the ANN model as the base model. The input management and the lighting control components were added to the ANN base model to create the FPGA Simulink system model as presented in Fig. 10.

Fig. 10 FPGA Simulink system model

Predefined data sets were created for the sun model and one can be selected in the simulation, as presented in Fig. 11. Two data sets containing theoretical values were made to represent extreme values of sunlight. The other four data sets come from the PAR data gathered in Dai-Yun organic farms, Taiwan, to represent natural sunlight PAR values. Two data sets were made from winter data with low and high values of sunlight. Two data sets were made from summer data with low and high values of sunlight.

Fig. 11 SUN Simulink model

The external hardware representation model blocks for the PAR sensor (using a linear model) and the lighting system (model: Philips GreenPower LED toplighting module Deep Red / White MB. Photon Flux: 440 µmol/s. Power: 200 Watts) on the output side were created [8]. The lighting system Simulink model used PAR supplementation value of 400 µmol/s (considering 90% of the rated value) and with power consumption of 200 watts. The FPGA-in-the-loop verification process linked Simulink and Altera Quartus II for the HDL code generation, analysis and synthesis, placement and routing, assembly, and timing analysis. The ‘.sof’ programming file was generated to load the FPGA-in-the-loop Simulink model into the actual FPGA device (Model: Altera Cyclone V 5CSEE5F31C6). As shown in fig. 12, the complete working environment Simulink system model was formed with the actual FPGA device (represented by an FPGA illustration in fig. 12) physically connected using the JTAG input/output data stream (USB port) in the FPGA-in-the-loop block. The simulations and testing were done in Simulink.

Fig. 12 Working environment Simulink system model
As a summary, the system design follows this optimization algorithm:
1. Accepts target DLI / energy saving mode, light-on schedule, light-off schedule from the user and PAR reading data from the sensor every hour.
2. Computes for the current DLI by averaging the hourly PAR data received.
3. Neural network receives target DLI supplementation level, light-on time, and the computed actual DLI.
4. System partitions the time (24 hours) into three time frames. First time frame starts from 0:00 to the light-off time. Second time frame is from light-off time to the light-on time. Third time frame begins at the light-on time and ends at 0:00.
5. System retains the first time frame, thus, maintaining the light-off time.
6. Neural network adjusts the light-on time initially set by the user based on the computed current DLI and the remaining achievable PAR values to accomplish the target DLI supplementation initially set by the user.
7. The neural network outputs the optimized number of hours of lighting operation on the third time frame, giving priority to the target DLI. It pushes the operation towards time 0:00 as reference to avoid the average daily electrical peak hours (16:00 to 20:00).
8. System output controls the lighting operations by turning on and off the lamp based on the resulting optimized light operating hours on the third time frame.

IV. RESULTS

Test results were presented in Table III showing the performance of the designed system. Test conditions were set for sun data used (PAR values), input target DLI / energy saving mode, light-on and light-off schedule. System output were tabulated as system-adjusted light-on time, actual DLI achieved, total lighting hours, energy used and energy saved.

Tests 1 and 2 used theoretical low and high sun data values representing extreme conditions on daytime. Tests 3 to 6 used real sun data for the dates January 9, July 31, Aug 5 and December 8 in 2014 acquired from the database in Dai-Yun Organic Farms, Taiwan. These data represented two winter and two summer observations. The input lighting schedule were varied accordingly based on the usual schedule done by the growers.

These results were obtained from the tests done through simulation using the working environment Simulink system model (Fig. 12). The energy used and saved, expressed in kWh, were computed by getting the product of the lamp power usage (200 watts for 400 µmol/s of PAR) and the total actual lighting hours. Plotting the time of the day versus the DLI (hourly PAR values), for the lamp PAR output and the DLI value monitoring for the entire day are shown in Figs. 13 to 18 for the six tests respectively.

<table>
<thead>
<tr>
<th>Test Conditions</th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
<th>Test 4</th>
<th>Test 5</th>
<th>Test 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sun data used</td>
<td>Low</td>
<td>High</td>
<td>Jan/9/14</td>
<td>Jul/31/14</td>
<td>Aug/5/14</td>
<td>Dec/8/14</td>
</tr>
<tr>
<td>Energy saving mode</td>
<td>High (3)</td>
<td>Low (1)</td>
<td>High (3)</td>
<td>Low (1)</td>
<td>Average (2)</td>
<td>High (3)</td>
</tr>
<tr>
<td>Target DLI value (µmol/s)</td>
<td>70-140</td>
<td>230-300</td>
<td>70-140</td>
<td>230-300</td>
<td>140-230</td>
<td>70-140</td>
</tr>
<tr>
<td>Light-On schedule</td>
<td>16:00</td>
<td>17:00</td>
<td>16:00</td>
<td>18:00</td>
<td>17:00</td>
<td>17:00</td>
</tr>
<tr>
<td>Light-Off schedule</td>
<td>6:00</td>
<td>4:00</td>
<td>6:00</td>
<td>4:00</td>
<td>5:00</td>
<td>5:00</td>
</tr>
</tbody>
</table>

In the first test, the system was able to adjust the light-on time from the initial setting of 16:00 to time 22:00 as shown in the left graph of Fig.13. The target DLI value of 70 to 140 µmol/s was met by achieving an actual DLI of 138 µmol/s at the end of the day, as seen in the right graph of Fig. 13. As a result, the lighting had only operated for 8 hours instead of 14 hours, thus, the lighting system only used 1.6 kWh of energy and saved 1.2 kWh.

In test 2, with high theoretical values of sun data, low energy mode was selected to have a high target DLI supplementation. The system was not able to adjust the light-on time, instead retained it and maximized the initial lighting schedule to give priority to achieving the high target DLI. The actual achieved DLI value was 267 µmol/s. So as a result, no energy saving was made, instead, used up the full 2.2 kWh for 11 hours of operation from time 17:00 to 4:00. For this test, the turning on and off of the lamp and the DLI behavior of the entire day can be seen in Fig. 14.
Test 3 used real sun data for January 9, 2014. Conditions were set to low target DLI and a lighting schedule of 16:00 to 6:00. Since low target DLI corresponded to high energy saving mode, the system was able to save 1 kWh of energy by adjusting the light-on time to 21:00 (Fig. 15), thus, successfully achieving an actual DLI value of 137 µmol/s.

Test 4 showed the output in test 4. The conditions set were quite similar with test 2 but at this point, using real sun data observed in July 31, 2014 and the lighting schedule was turned on late and turned off early resulting to initially less lighting hours. The system was not able to save energy and it was also not able to meet the high target DLI between 230 – 300 µmol/s, instead it achieved only 176 µmol/s (falls under average target DLI), around 54 µmol/s short of having at least 230 µmol/s. This was caused by very low PAR values during daytime and the user’s input of lesser lighting hours.

In test 5, Aug 5, 2014 sun data were used. The system was capable of achieving 197 µmol/s for the entire day which fell within the selected average target DLI range. Even average saving mode was selected, no energy saving was made because the system also used up the entire 12-hour lighting operation to prioritize the average target DLI.

Sun data in December 8, 2014 were used in test 6. This time, low target DLI supplementation was selected with initial lighting schedule of 12 hours from 17:00 to 5:00. The system shifted the light-on time from 17:00 to 22:00, thus, adjusting to an actual 7 hours of lighting operation. The system was able to save 1 kWh of energy on its adjusted lighting hours, achieving 119 µmol/s of low target DLI. The lamp (left graph) and DLI monitor (right graph) output are shown in Fig. 18.

V. CONCLUSION

In this study, the designed system performed consistently in the various tests done. It was able of accepting input lighting schedule and target DLI supplementation from the user and the data from the PAR sensor. It was successful in giving priority on achieving the target DLI supplementation chosen by the user that corresponds to the selected energy saving mode. The system was able to keep the adjusted light-on time within the boundaries of the lighting schedule initially set by the user. Actual energy saving was constrained by the accumulated PAR during daytime and the input lighting schedule. High PAR values during daytime contribute to reaching a significant amount of saved energy. In the contrary, low PAR values during daytime limit the energy saving. According to the test results, it was capable of saving significant amount of energy when low target DLI supplementation was selected. But no energy saving was made when high to average target DLI supplementation was selected because the system tend to maximize the initial lighting operation schedule to meet the demand for high target DLI value.

The system, in the future, may be tested using actual hardware for the PAR sensor and the lighting system.

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