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# Designing and Implementing a Novel Solar Panel Tracker Leveraging Reinforcement Learning Technique

Emma Li[1], Brian Li[1] and Hui Li[#]

[1]Mission San Jose High School, Fremont, CA, USA
[#]Advisor

## ABSTRACT

As of today, the average efficiency of household solar panels is less than 20 percent, so less than 20 percent of solar energy is converted into household electricity. Our goal is to explore various techniques that not only enhance this efficiency but also are scalable to households. We plan to use reinforcement learning technique that provides the centralized intelligence for controlling a large set of trackers for household solar panels. Reinforcement learning is a proven machine learning technique to explore unknown environments while maximizing a reward. This is desirable because each household's environment is different. Furthermore, the tracker is purely software-driven with no dependency on specialized hardware. This makes it simple, easy to deploy, and suitable for large-scale application. In this project, we designed and implemented a reinforcement learning technique for a solar panel tracker that adjusts the solar panel's orientations to maximize the sun ray receptance. The tracker explores an optimal orientation, taking into account of the environmental variations such as the sun's location and shade caused by surrounding obstacles. To demonstrate the effectiveness of our solution, we placed two identical solar panels side-by-side. One is mounted on our solar panel tracker; the other is stationary. We then collected voltage measurements from both solar panels at identical time intervals between 8 AM to 5 PM each day. We repeated the same benchmark testing for several days. Our results have shown that the solar panel on our smart tracker consistently offers higher electricity voltage output than the one without.

## 1. Introduction

According to IGS Energy (IGS Energy, 2000-2021), the average household solar panel efficiency is fairly low, less than 20 percent and this is mainly due to the higher system cost for producing solar panels with higher efficiency. This motivates experts and researchers to look for other ways of enhancing solar panel efficiency. Hannah Glenn (Glenn, 2018) summarized the factors that affect solar panel efficiency and among which, environmental factors such as sun movement and various obstacles including dust, clouds and trees all play an important role. Taking into account of such environmental factors, solar trackers were introduced to dynamically adjust the orientation of solar panel with the aim to improve solar panel's efficiency.

There are various existing solar trackers, each using a different technique. For example, Essam Tawfik El Shenawy et. al. (Shenawy et. al. 2012) designed the solar tracker that leverages a neural network. As shown in Figure 1, it works based on the neural database guessing the output of the solar panel and is considered fully trained when this output and the real output are equivalent. The limitation of this approach is the need for pre-training, and that it is only applicable in a certain environment, the one in which it was pre-trained.

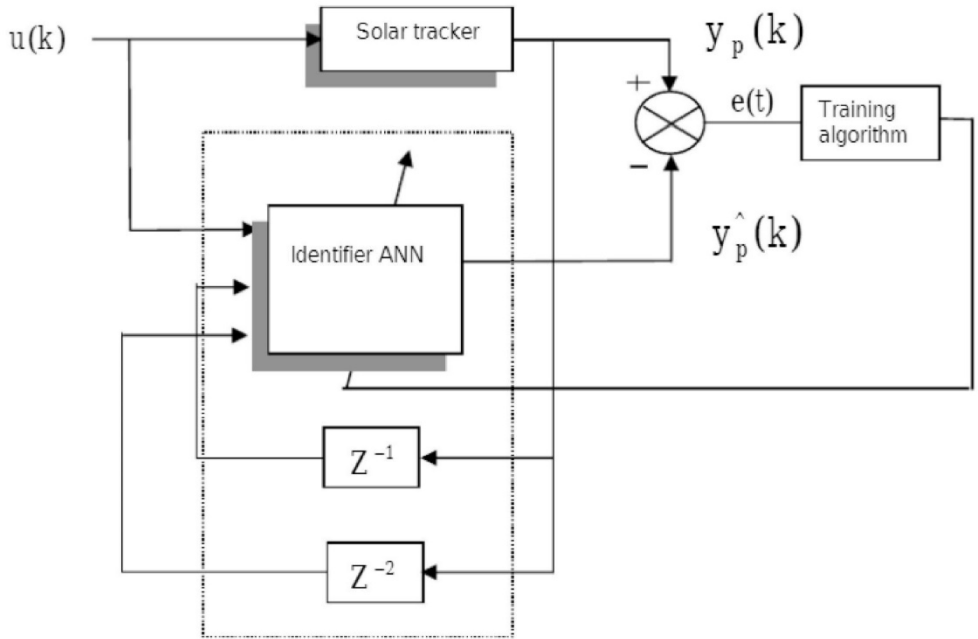


**Figure 1.** Neural network schematic view.

Arshadi Abas (Abas, 2016) presented the solar tracker that uses light-dependent resistor (LDR) sensors, one on each side, as shown in Figure 2. Such sensors decrease in resistance under high light intensity and increase in resistance under low light intensity. It is believed that when the opposite sensors have equal resistance, then the solar panel orientation is optimal. However, the disadvantage of this solar tracking system is that it is not tailored to environmental variations, meaning that the solar panel can very well adjust to an area that is completely dark and still have the opposite sensors with equal resistance.

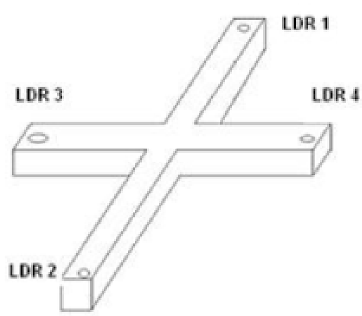


**Figure 2.** Position of the light-dependent resistors.

Zomeworks (Zomeworks) came up with the solar tracker that utilizes a special liquid that increases in weight as it is heated. As shown in Figure 3, there are two containers, one on each end of the solar panel, that contain this liquid. When the weights of these two containers are equal, then the solar panel will be facing directly towards the sun. However, such a liquid is expensive and not scalable for household applications.

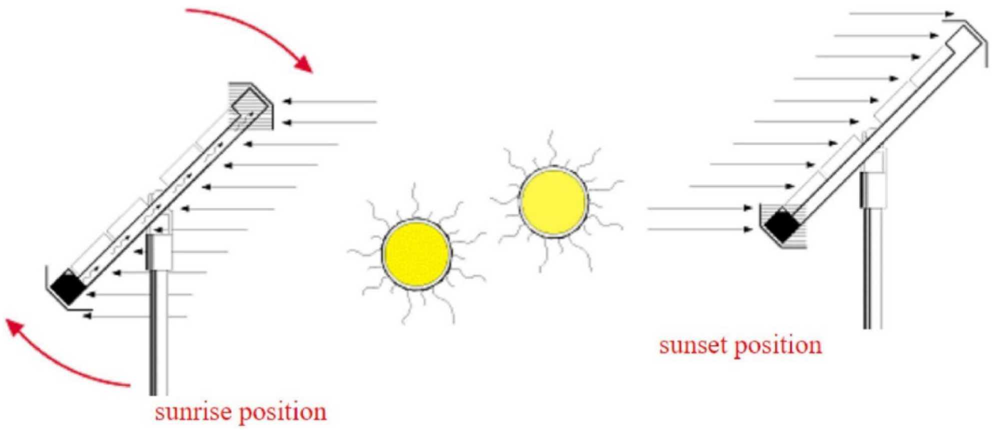


**Figure 3.** Generic sunrise and sunset positions.

Here, we introduce a solar tracker that leverages a reinforcement learning technique for its underpinning controlling intelligence and aims to improve solar panel's efficiency for the household usage. Reinforcement learning is a proven machine learning technique to explore an unknown environment with the goal of maximizing a reward. This is particularly desirable because each household's environment is different. On top of that, the tracker's controlling mechanism is purely software-driven with no dependency on any specialized hardware components like some existing designs illustrated above. This makes each tracker simple and easy to deploy. It is also possible to use a centralized software to control thousands of such trackers. Therefore, such approach can be scalable for household usage from deployment and operation perspectives as well.

## 2. Methods

### 2.1 What is Reinforcement Learning?

Reinforcement learning is a branch of machine learning in which an agent receives a state from an environment and performs actions to change the state (ADL, 2018). Figure 4 provides the illustration. Those actions will result in a reward, and based on the reward, the agent will decide its next action. The goal is to maximize this reward. There are two forms of actions: exploitation and exploration. Exploitation is when the agent performs the same action over and over again after discovering that this specific action will always result in a positive reward. Exploration is when the agent tries a new course of action every time. Henceforth, there is a possibility of getting an even higher reward, but also a risk that the reward would be lower.

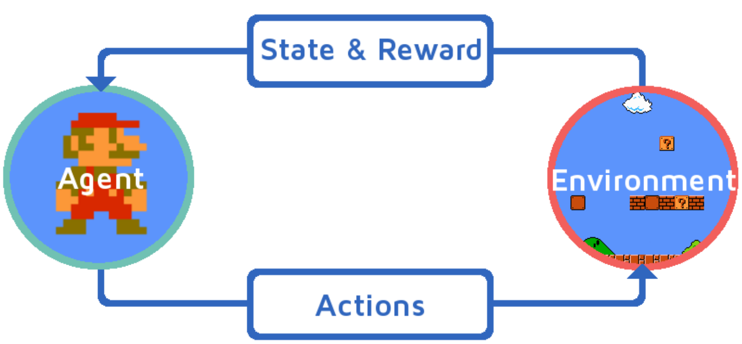


**Figure 4.** Reinforcement learning illustration.

## 2.2 Our Approach

We have developed a new reinforcement learning technique for controlling our solar tracker to maximize solar panel efficiency. Such an approach offers effectiveness and adaptiveness because it takes into account environmental variations of the sun's location, wind condition, humidity, the shade and light reflection caused by obstacles.

### *2.2.1 Apply Reinforcement Learning to Solar Tracker*

For our solar tracker, the environment includes the sun, wind condition, clouds, dust, trees, and other obstacles, and the tracker system itself. The state is the current solar panel orientation and the reward is the solar panel output voltage change after an action. The action set includes the incremental clockwise and counterclockwise rotation of both a base motor and a tilt motor, as shown in Figure 5. The base motor rotates the solar panel about its vertical (out-of-plane) axis while the tilt motor rotates the solar panel about its longitudinal axis. These rotations offer the opportunity for our reinforcement learning algorithm to seek an optimal orientation for the solar panel at any given time.

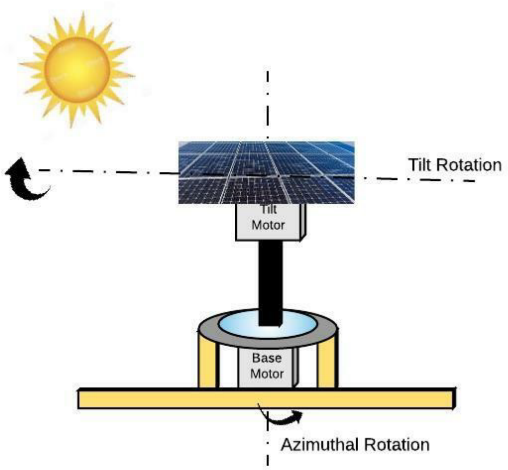


**Figure 5.** Design for solar tracker with two motors.

Figure 6 illustrates the basic reinforcement learning algorithm for our tracker. Every time the tracker takes the actions, it will start the cycle with consecutive tilt motor rotations to re-adjust its tilt orientation. Then, this is followed by consecutive base motor rotations to re-adjust its horizontal orientation. The cycle is repeated as long as any base motor rotation results in a positive reward. The consecutive rotations for either tilt motor or base motor will continue as long as the most recent rotation yields a positive reward. The rotation direction for these consecutive rotations is determined at the beginning. The clockwise direction will be tried first, and if it yields a negative reward, the counter-clockwise direction will be tried. After some preliminary experiments, the incremental tilt motor rotation is set to 3 degrees and incremental base motor rotation is set to 5 degrees.

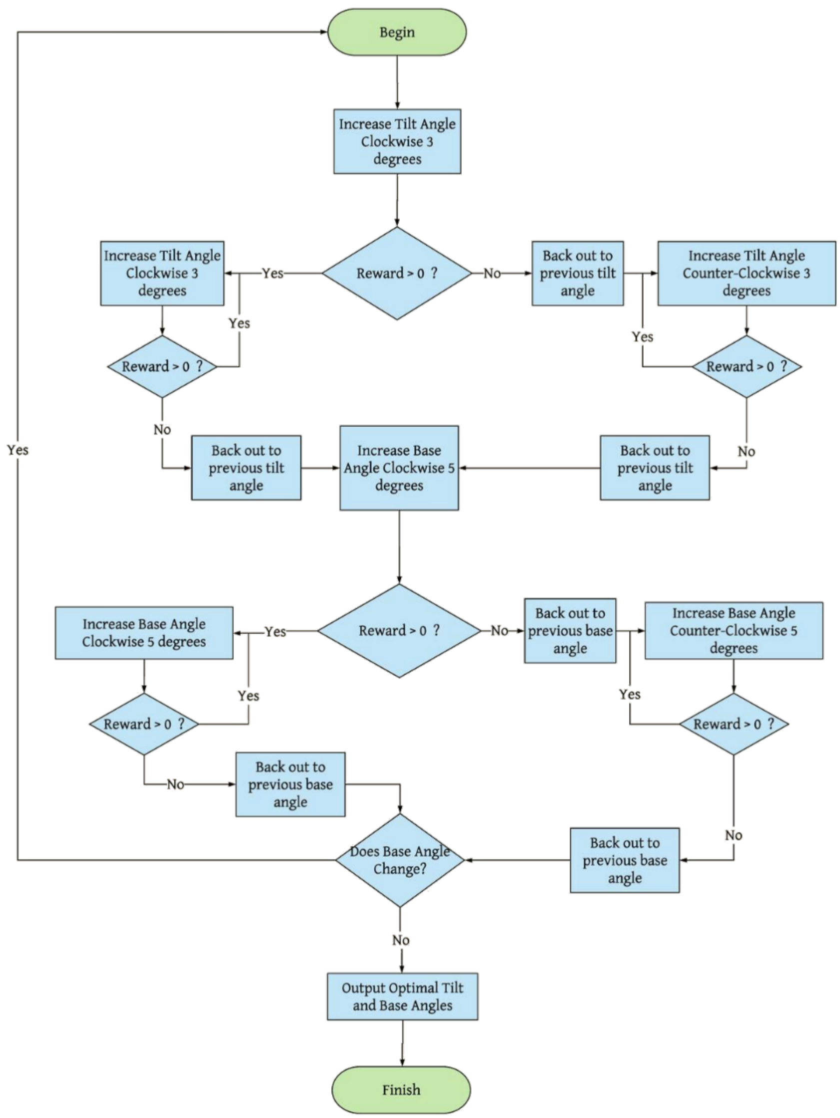


**Figure 6.** Basic reinforcement learning algorithm for solar tracker.

### *2.2.2 Enhance with Exploration*

During our experiments, we observed that occasionally the smart tracker solar panel will get trapped into a wrong position from morning on. Because of that, the entire trial yields a negative percentage gain, and we consider it as a failure trial. The reason for such failure is that the basic reinforcement learning algorithm is completely reward-driven, heavily focusing on exploitation. The solar panel tracker can be misled into a wrong position by local reward guidance. To resolve this issue, we enhance the basic algorithm with exploration effort by using two new explorative actions:

- Composite actions: *perform two actions consecutively*
    - Base-cw-Tilt-cw action: base motor clockwise rotation action followed by a tilt motor clockwise rotation action
    - Base-cw-Tilt-ccw action: base motor clockwise rotation action followed by a tilt motor counter-clockwise rotation action

- Sweep action: sweep through 60-degree range of tilt angle centered at the current angle position and position solar panel to the tilt angle that gives the maximum voltage output.

With the above exploration actions, we extend the basic reinforcement learning algorithm with the new workflow as illustrated in Figure 7. Under this new workflow, each time the basic algorithm is completed, we check if the solar panel gets repositioned or not. If it does not get repositioned, to counteract the situation that the solar panel could be potentially trapped, a composite action is launched. If a positive reward is received, the basic algorithm is kicked in again based on the new position; otherwise, a sweep action is launched which will forcefully explore 60-degree tilt angle range centered around the current tilt angle position and re-orient the solar panel to the angle position corresponding to the maximum voltage output. We recorded the voltage outputs before and after these explorative actions being launched so that we can quantitatively compare the effectiveness of this adjusted algorithm.

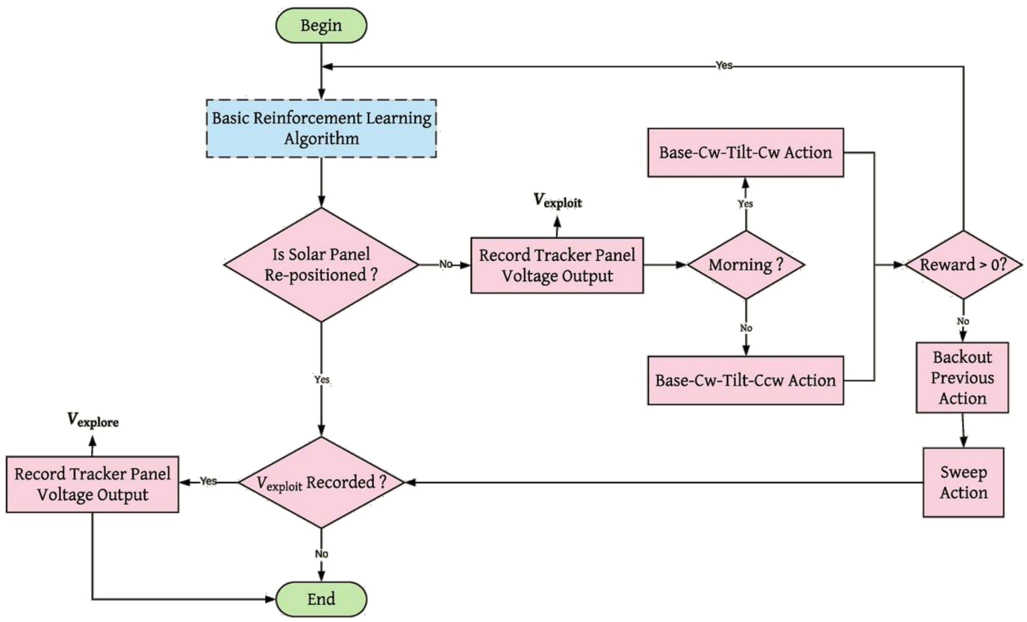

**Figure 7.** Extend basic reinforcement learning algorithm with exploration.

## 3. Experiment Conditions

### 3.1 Apparatus

To demonstrate our idea and its underpinning design, we built a physical apparatus shown in Figure 8 that we conducted all the experiments on. Our device mainly consists of two solar panels mounted side-by-side: a baseline solar panel with a fixed orientation throughout the experiment and a smart solar panel mounted on our solar tracker. The reinforcement learning algorithm is running on an Arduino board. We also use the Arduino board to control both tilt and base motors and collect voltage outputs from both baseline and smart tracker solar panels. The collected voltage data generated by the solar panels are output into the serial monitor running on a laptop and those data are transferred into Google sheet for further analysis after each trial is completed.

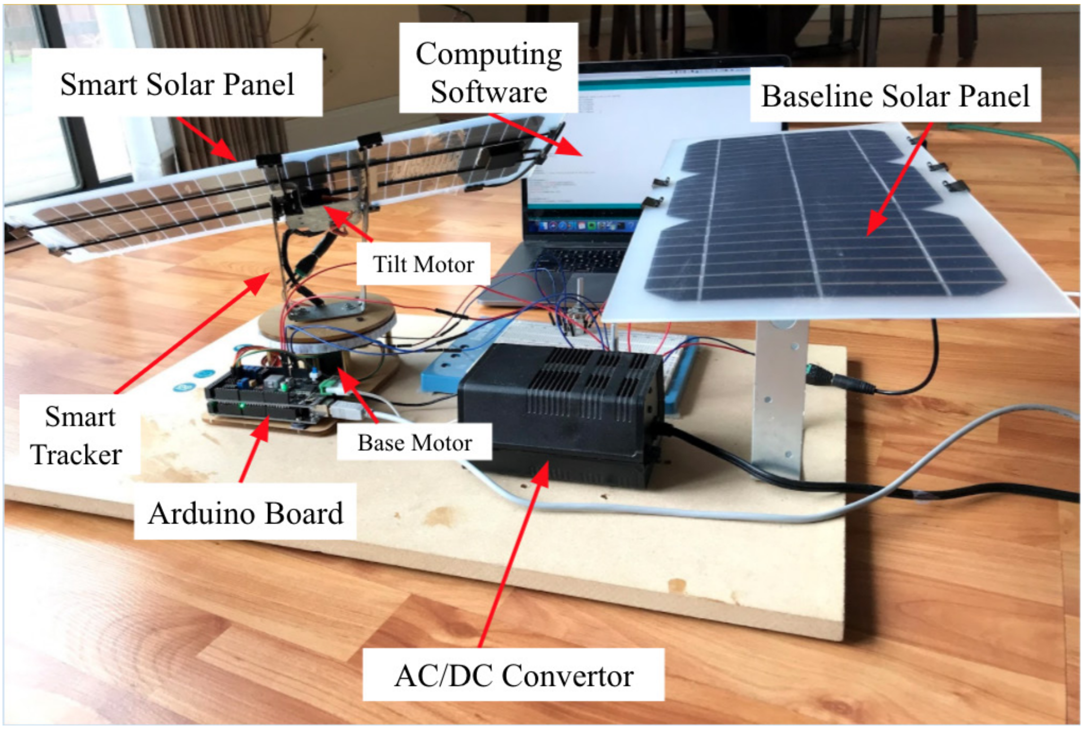


**Figure 8.** System Setup

## 3.2 Measurements

We have conducted our experiments for both winter and spring seasons. For the winter season, we choose our experiment duration from 8 am to 5 pm for each day. For the spring season, because of the daylight-saving time change, we extend our experiment duration from 8 am to 7 pm for each day. We consider each daily experiment as a trial. Every fifteen minutes, the smart tracker will go through the reinforcement learning algorithm, and right after that, we collect data. Each data point is denoted as a 3-tuple (t, Vb, Vs) where t is the timestamp, Vb is the baseline solar panel voltage, and Vs is the smart solar panel voltage. There is a total of 36 data points per winter trial, and a total of 44 data points per spring trial. We have conducted 5 winter trials and 16 spring trials. To quantitively measure the smart tracker's solar panel efficiency improvement, we introduce a measurement called daily voltage output percentage gain, which measures the total voltage output percentage difference between the smart tracker solar panel and baseline solar panel for each trial:

$$\mathrm{Psb} = \frac{\sum_{i=1}^{T} \mathrm{Vs_i} - \sum_{j=1}^{T} \mathrm{Vb_j}}{\sum_{j=1}^{T} \mathrm{Vb_j}} \times 100\%$$

Note that T is the total number of collected data points per trial (36 for winter trials and 44 for spring trials). The following formula gives us the average percentage gain among all winter trials or spring trials:

$$\mathrm{AVE_{Psb}} = \frac{\sum_{i=1}^{N} \mathrm{Psb_i}}{\mathrm{N}} \text{ (Average of N Trials)}$$

To show the consistency of such improvement, we further calculate the standard deviation as the following:

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$$\mathrm{VAR}_{\mathrm{Psb}} = \frac{\sum_{i=1}^{N}(\mathrm{AVE}_{\mathrm{Psb}} - \mathrm{Psb}_i)^2}{N}$$

$$\mathrm{STD}_{\mathrm{Psb}} = \sqrt{\mathrm{VAR}_{\mathrm{Psb}}}$$

## 3.3 Obtaining Voltage Output

The particular challenge we had during our experiment was how to obtain the voltage output. The reason is that the solar panel voltage output is 18V, which exceeds Arduino's maximum analog input voltage of 5V. Therefore, we used a potentiometer to scale down the solar panel voltage output to within 5V. However, the potentiometer scaling is nonlinear because the solar panel itself has resistance and its resistance decreases as the light intensity and the corresponding voltage output value increase. Figure 9 illustrates the relationship between the voltage measured by Arduino ($V_{12}$) and the solar panel voltage output ($V_{ab}$):

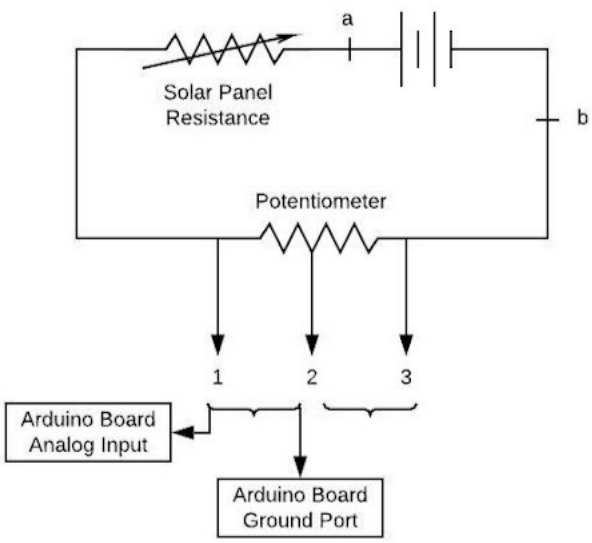


**Figure 9.** Circuitry Diagram

To create some safety cushion for Arduino board, we scale the solar panel maximum voltage output from *18V* to *4.5V*. To calculate the potentiometer resistance ratio, we divide the resistances from 1 to 2 and 1 to 3 to get $\frac{R_{12}}{R_{13}} = \frac{4.5}{18} = \frac{1}{4}$. By applying Ohm's Law, which states that V = IR, we obtain the ratio between $V_{ab}$ and $V_{12}$:

$$\frac{V_{ab}}{V_{12}} = \frac{V_{a1} + V_{13}}{V_{12}} = \frac{I(R_{a1} + R_{13})}{V_{12}} = \frac{R_{a1} + R_{13}}{R_{12}} = 4 + \frac{R_{a1}}{R_{12}}$$

where $R_{a1}$ is the solar panel resistance, and its value changes with each different value of $V_{12}$. The above formula further indicates that the mapping from $V_{12}$ to $V_{ab}$ is non-linear.

To resolve this issue, a calibration is conducted on sample pairs of $V_{12}$ and $V_{ab}$ as shown in Table 1. The tracker panel and baseline panel need to be calibrated separately because their intrinsic resistances $R_{a1}$ are different. Arduino has a 10-bit analog to digital converter that maps voltages (0V, 5V) to integers (0, 1023).

**Table 1.** Voltage Calibration

| Tracker Panel | | | | Baseline Panel | | | |
|---|---|---|---|---|---|---|---|
| Solar Panel Open Voltage ($V_{ab}$) | Arduino Output Voltage ($V_{12}$) | Solar Panel Open Voltage ($V_{ab}$) | Arduino Output Voltage ($V_{12}$) | Solar Panel Open Voltage ($V_{ab}$) | Arduino Output Voltage ($V_{12}$) | Solar Panel Open Voltage ($V_{ab}$) | Arduino Output Voltage ($V_{12}$) |
| 4.02 | 3 | 11.01 | 129 | 4.04 | 15 | 11.00 | 250 |
| 5.01 | 4 | 12.01 | 297 | 5.02 | 22 | 12.01 | 436 |
| 6.01 | 7 | 12.99 | 569 | 6.00 | 29 | 12.97 | 601 |
| 7.01 | 10 | 14.01 | 665 | 7.01 | 44 | 14.00 | 691 |
| 8.00 | 16 | 14.99 | 727 | 8.01 | 68 | 15.00 | 748 |
| 9.05 | 34 | 16.01 | 797 | 9.00 | 99 | 16.01 | 806 |
| 10.01 | 65 | 16.51 | 827 | 10.01 | 150 | 16.50 | 838 |

With the above calibration, we then determine $V_{ab}$ based on any $V_{12}$ measured by Arduino with the following steps:

1. Identify two closest calibration pairs: ($V_{12L}$, $V_{abL}$) with ($V_{12H}$, $V_{abH}$) with $V_{12L} \leq V_{12} \leq V_{12H}$.
2. Use linear interpolation formula: $V_{ab} = V_{abL} + (V_{12} - V_{12L}) \cdot \frac{V_{abH} - V_{abL}}{V_{12H} - V_{12L}}$

## 4. Experimental Challenges

We tackled quite a few challenges while conducting our experiment. One issue was regarding how to obtain the voltage output as described above. Other challenges are noted here:

- Wires connecting tilt motor to Arduino board initially got entangled and prevented the tracker from exploiting base angles. To solve this problem, we drilled center holes on the mounting plate and rotational platform, and routed the wires through the holes.
- The base motor is a continuous rotation servo, so it does not offer direct angle control. We calibrated the relationship between the rotation time and the sweeping angle and used the rotation time to indirectly control the target base angle.

## 5. Experiment Results

### 5.1 Daily Voltage Output Results on Winter Trials

Below shows the results for the winter trials. Figure 10a depicts the comparison between the smart solar panel and baseline solar panel for the best trial, achieving a daily voltage output percentage gain of 22.45%. Figures 10b and 10c summarize the results for all winter trials, with the average percentage gain being 17.12% and the standard deviation being 4.61%.

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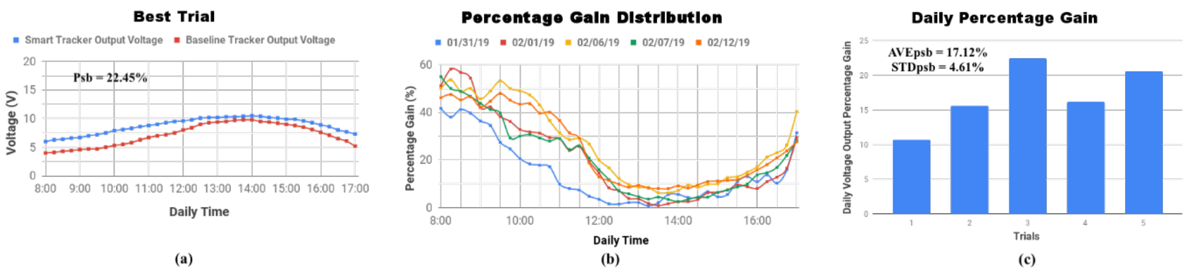



**Figure 10.** (a) Best trial comparison, (b) winter trial percentage gain distribution, (c) winter trial daily voltage output percentage gain

## 5.2 Enhanced with Exploration

As mentioned previously, an issue that we encountered with our solar tracker was that the solar panel would occasionally get trapped in the wrong position starting from the morning. The solution we proposed was to enhance our current algorithm with exploration efforts. To demonstrate the effectiveness of the exploration, we conducted the first half of our spring trials without exploration and the second half with exploration. The graph on the left of Figure 11 shows a trial where the smart solar panel got trapped in the morning, resulting in a lower output voltage than the baseline solar panel. The chart on the right summarizes the daily voltage output percentage gains of the first half of the spring trials without exploration. Two of the trials highlighted in red had negative percentage gains, which means that the tracker performed worse than the stationary solar panel.

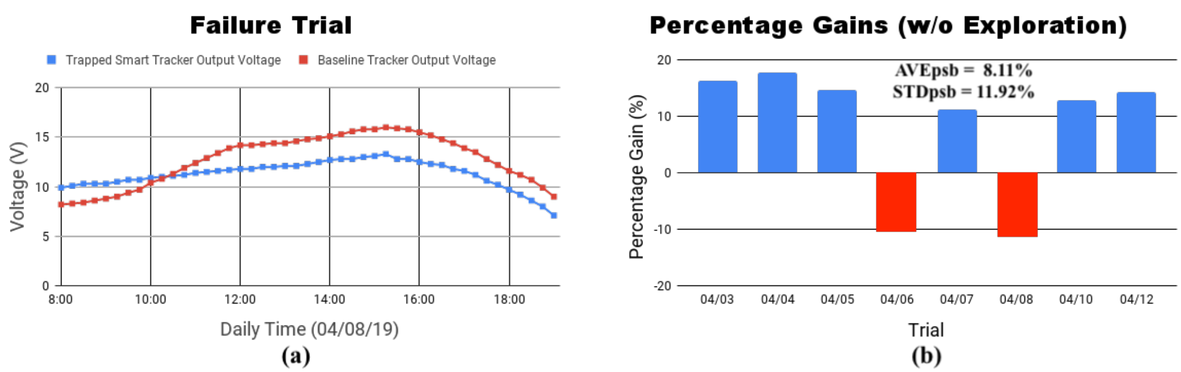
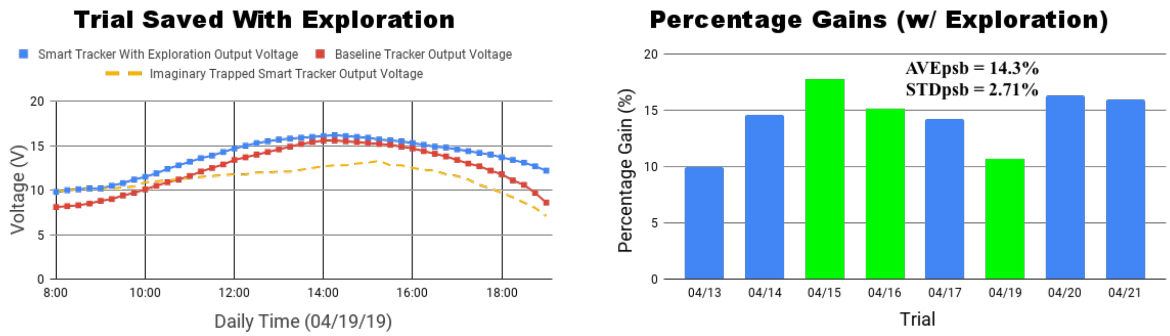



**Figure 11.** (a) Failure trial comparison, (b) percentage gains per trial without exploration

Figure 12 demonstrates the effectiveness of this new and improved algorithm leveraging exploration. As shown by the left graph, the exploration saved the failed trial by raising the voltage output of the smart tracker above the baseline solar panel's voltage output. In the graph on the right, for the trials on days 04/15, 04/16, and 04/19, the smart solar panel became trapped from the start, but the exploration effort saved the trial. This allowed the tracker to recover, and ultimately brought the daily voltage output percentage gain up above zero, as highlighted in green.




(a) (b)

**Figure 12.** (a) Exploration trial comparison, (b) percentage gains per trial with exploration

## 6. Discussion and Conclusion

We have demonstrated a solar tracking system that leverages a reinforcement learning technique. Our experiment data consistently shows positive daily voltage output percentage gains from the smart solar tracker throughout our winter and spring trials. With, on average, a nearly 20% efficiency gain, this approach is clearly effective. In addition, the spring trials particularly proves that our exploration extension to the basic reinforcement learning algorithm is effective which not only brings up the overall efficiency gain but also enhances the consistency of the gain (average Psb increasing from 8.11% to 14.3% while standard deviation decreases from 11.9% to 2.7%).

We can also make the further observations based on the charts listed in experiment results:

- The efficiency percentage gains in the morning and evening are greater than the daily peak temperature time window, which is usually centered around noontime.
- Spring trials with warmer days have smaller daily efficiency percentage gain compared with winter trials.

We believe there are two main contributing factors to explain this:

- The baseline solar panel is positioned facing up vertically, thus likely to output close to optimal voltages during peak temperature hours. A warmer day also tends to have longer peak temperature time window.
- As the temperature or light intensity goes higher, both the smart and baseline solar panel voltage outputs are higher, so it is expected for the percentage gain from the smart solar panel to be lower.

## 7. Acknowledgments

This paper is based off of our science fair project that we conducted in 2019. Special thanks to our school principal Corey Brown and the science fair director of our home county Patti Carothers for offering gracious help and encouragement during the entire research process. For reference, all of our code and videos that we used to verify the solar tracking system can be found [here.](here.)

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