Proceedings of CHT-17
ICHMT International Symposium on Advances in Computational Heat Transfer
May 28-June 1, 2017, Napoli, Italy
CHT-17-310

# SURROGATE-BASED OPTIMIZATION OF A FOLDED SOLAR CELL STRUCTURE WITH ENHANCED OPTICAL EFFICIENCY

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## ABSTRACT

One of the most effective approaches to improving the efficiency of a solar cell is to alter the geometric structure of the panel. Convex and folded structures can enhance absorption of solar radiation in crystalline cells by reducing average reflectance from the surface. In order to properly design these modified surface geometries, precise optical radiation simulations such as ray tracing optics must be executed. Monte Carlo ray tracing simulations can be extremely time-consuming, and therefore thorough optimization that relies on them is inefficient. One way to overcome the aforementioned challenge is to utilize surrogate models. With the help of tools from machine learning, data-driven surrogate models can be developed and learned which directly approximate the average result of a large scale Monte Carlo simulation for every arbitrary set of input values, using a simple forward function. The approximate model can then be used for optimization instead of original MC simulations. Such a framework is called surrogate-based optimization. This work applies surrogate-based optimization to ray tracing optical simulations in order to improve the efficiency of silicon solar panels using a folded surface. We study optimal design of the geometry of a stationary solar cell structure with a three-folded surface. The efficiency of the cell is measured with respect to average radiation angle with standard AM1.5 solar irradiance, and the design goal is to maximize the average optical absorptivity of the radiated sunlight in the panel. We use neural networks as surrogate models and demonstrate that the model can accurately estimate spectral absorptivity of a random geometry, and furthermore, it can be reliability used in optimization. Results of optimization using the proposed surrogate model suggest that the optimal panel with folded surface has an improved efficiency over that of the flat panel with the same length by as large as 13%.

## NOMENCLATURE

| | |
|---|---|
| $\alpha_1$ | Left flap length fraction |
| $\alpha_2$ | Right flap length fraction |
| $\theta_1$ | Left flap tilt angle |
| $\theta_2$ | Right flap tilt angle |
| $\theta$ | Solar angle |
| $\omega$ | Wavelength |
| $A(\mathbf{g})$ | Optical absorptivity (efficiency) |
| $A_\theta(\mathbf{g})$ | Spectral absorptivity |

| | |
|---|---|
| $A_{\theta,\omega}(\mathbf{g})$ | Spectral and angular absorptivity |
| $\mathbf{g}$ | Geometry vector |
| $F(\cdot)$ | Functional form of spectral absorptivity |
| $\hat{F}(\cdot)$ | Surrogate function for spectral absorptivity |
| $I_{\mathrm{AM15}}(\omega)$ | Solar irradiance |
| $L$ | Length of panel |
| $L'$ | Cross section length of solar radiation on the cell |
| $n_\omega$ | Real refractive index of silicon |
| $R$ | Reflectance factor of silicon |
| $R_s, R_p$ | s-polarized and p-polarized reflectance of silicon |

## INTRODUCTION

Silicon-based solar panel is a critical power supply for terrestrial use. In recent years, large efforts have been dedicated to improving the power conversion efficiency of solar cells, which generally follow three main directions: 1) design and application of new materials, 2) advanced cleaning methods and 3) use of novel structures and geometries. Among those, use of the flexible shapes of solar cells is one of the most promising methods to achieve improved performance.

Traditionally, solar cells consist of multiple flat pieces on the same plane due to ease of fabrication and analytical study. Recent studies of textured, folded or flexible solar cells demonstrate potential gain that can be acquired from such structures. In previous studies, a number of researchers have investigated the effect of various shapes or structures on the solar cell performance. For instance, Garifulina et al. studied three different shapes of solar cell modules, including modeling and analyzing rectangular, circular, and zigzag cells [1]. Based on the geometry optimization results, it was demonstrated that both the geometrical parameters and the number of modules have significant influence on the output efficiency. In addition, maximum efficiency was achieved when the solar cell is in a zigzag shape with the cell width of 4 mm, because electric current on average flows a shorter path compared to the rectangular and circular shaped modules. Andersson et al. modeled a folded (V-shaped) organic solar cell using the finite element method [2]. The results revealed that folding the panel increases absorbed radiation for both single and tandem cells. Tvingstedt et al. also proposed a structure with folded two planar but spectrally different cells facing each other, and the resulting structure gave an improvement of power conversion efficiency by a factor of 1.5 - 2.1 [3]. Bernardi et al. focused on the solar energy in three-dimensions [4]. In their research, the three-dimensional photovoltaic structures was shown to generate higher energy densities (i.e. energy per base area) by a factor of 2 to 20 compared to the equivalent flat panels, and the proposed technology was also shown to reduce the effect of seasonal and latitude variations on energy generation, with higher benefits in cloudy weather. A cube model with open top, made out of 9 solar cells was proved to be capable of improving the annual energy density generation by a factor of 2 – 3.8, compared to a flat horizontal panel. Guo et al. studied two- and three- dimensional folding of thin film solar cells [5]. The spherical and cylindrical-shaped silicon-based solar cells were constructed and their electrical performance improvement was investigated. The results revealed that these 3D structures, combined with other guiding principles result in improved devices that have lower costs and higher efficiencies.

Efficiency improvement in crystalline silicon based is directly correlated with optical absorptivity. When solar radiation hits the surface of the cell, a fraction of the incident energy is reflected due to the mismatch between the refractive index of the underlying absorbing layer and air. The reflection index is not constant and depends on the angle of incident, wavelength and polarization of radiation. Furthermore, rays that hit the surface at a non-normal incident angle deliver less energy per unit of area. Solar tracking technology alleviates this issue by adjusting the tilt angle of the cell to the position of the sun, but they come at the cost of extra motion control mechanisms. Using folded structures and surface textures for fix panels is an alternative to solar tracking by reducing average reflectance. Textured and folded structures help reabsorb part of the reflected light and thus trap the incoming energy efficiently. Simulations of absorption/reflectance effects of light at textured and folded structures for various wavelengths and polarizations require accurate ray tracing Monte Carlo simulations. These simulations are often intense and time-consuming. Geometry design and optimization based on those calculations are even more cumbersome. To overcome this challenge, one can use *surrogate* models to estimate large scale MC simulation results using straightforward calculations. Such a model requires training and fitting with sufficiently large amounts of sample data, and is usually based on tools from machine learning.

Use of surrogate models to enhance design and optimization process in solar cells is not completely unprecedented, and has recently gained some attention. Most of the existing efforts in the literature for this approach are geared towards optimization of the new generation perovskite solar cells. For example, Ariyarit et al. proposed using Kriging surrogate model in conjunction with Generic Algorithm to facilitate faster optimization of crystalline structure in high efficiency perovskite cells [6]. Training data is collected in a so-called Design of Experiment procedure, and fit via a Kriging model, which can then be used to find optimal choices of spin-coating speed and MAI dripping time. Wodo et al. proposed a novel graph-based surrogate model to address the relationship between morphology and performance of organic solar cells [7]. Huang et al. used response surface method to establish the relation between the efficiency of dye-sensitized solar cells, electrolyte conductivity and tri-iodide diffusivity based on different electrolyte compositions [8]. Then, the optimal composition was found for maximum efficiency based on the proposed model. Some other previous work has studied the general electrical circuit behavior of a solar cell using surrogate models. For instance, [9] and [10] have independently modeled a solar cell output power delivery using radial basis function neutral networks, in order to study the characteristics of solar cells at different situations. In addition, several researchers have considered using surrogate models and learning algorithms to estimate and predict solar radiation spectrum [11,12].

In this paper, we use a surrogate-based optimization algorithm to maximize absorption efficiency of a three-folded solar panel. The proposed solar cell structure consists of three pieces of flat panels (one central flat panel and two side flaps) joint together with particular tilt angles. The efficiency of the solar cell is measured with respect to the average radiation angle and the standard AM1.5 irradiance. Accurate efficiency calculations can be achieved through Monte Carlo optical ray tracing simulations which require a large number of iterative calculations, especially when a wide spectrum of radiation and a range of incident angles are involved. The optimal design based on accurate ray tracing optics is therefore a time-consuming numerical optimization procedure that cannot be efficiently done. To resolve this issue, we propose using a surrogate model that approximates the spectral absorptivity of the cell, as a function of the geometry parameters and angle of radiation. We use artificial neural networks to learn the approximate model, and demonstrate that it can accurately estimate the spectral absorptivity over the out-of-sample data, and reliability used for optimization. Results of optimization using the proposed surrogate model suggest that the optimal panel with side flaps improves the efficiency of the flat panel with the same length by as large as 13%.

## THREE-FOLDED SOLAR CELL MODEL

The principle idea of our design is to improve the average efficiency of a solar cell with respect to changes in radiation angle by creating convexity in the absorbing panel. We propose a simple design that consists of three flat panels jointed together as depicted in Figure 1. The overall length of the panel is $L$. The panel is fixed (do not rotate) and its efficiency is compared with an equivalent flat panel of length $L$.

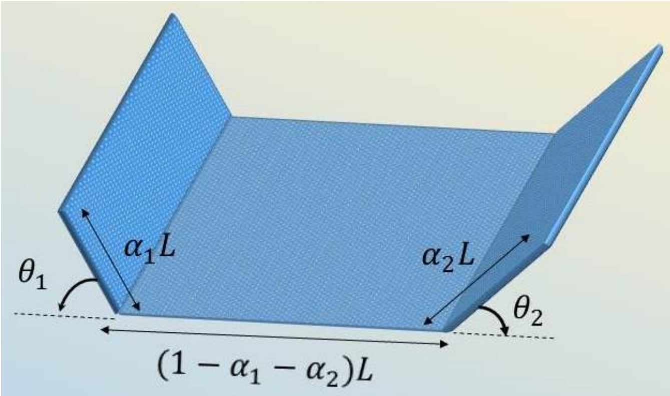


Fig. 1. Three-folded solar panel schematics.

The geometry of the cell is characterized by four parameters as follows:

1) $0 \leq \alpha_1 \leq 0.5$: Fraction of the left flap length
2) $0 \leq \alpha_2 \leq 0.5$: Fraction of the right flap length
3) $0 \leq \theta_1 \leq \pi/2$: Tilt angle of the left flap
4) $0 \leq \theta_2 \leq \pi/2$: Tilt angle of the right flap

We represent these parameters by a numerical vector called the geometry vector:

$$\mathbf{g} = (\alpha_1, \alpha_2, \theta_1, \theta_2) \tag{1}$$

The goal of optimization is to find the geometry vector **g** so that the optical efficiency (absorptivity) of the resulting cell is maximized.

## EFFICIENCY CALCUALTIONS

Optical efficiency (absorptivity) $A(\mathbf{g})$ for a particular geometry vector is defined as the amount of incident light absorbed in the silicon for solar radiation with standard air mass AM1.5 (shown in Figure 2). Mathematically, optical absorptivity (efficiency) of the cell for a range of incident angles $(0, \theta_{max})$ is defined as:

$$A(\mathbf{g}) = E_{0\leq\,\theta\leq\theta_{max}} E_{\omega\in\Omega}\big(A_{\theta,\omega}(\mathbf{g}) \times I_{\mathrm{AM1.5}}(\omega)\big) \tag{2}$$

where $E(\cdot)$ is the average notation, $I_{\mathrm{AM1.5}}(\omega)$ is the power spectrum of the AM1.5 solar irradiance at a particular wavelength $\omega$, $\Omega$ is the wavelength range where the majority of AM1.5 irradiance power resides, and $A_{\theta,\omega}(\mathbf{g})$ is the absorptivity of the solar cell for a particular wavelength $\omega$ and a particular incident angle $\theta$. When $A_{\theta,\omega}$ is averaged over the irradiance, it yields the absorptivity with respect to a particular angle, which we refer to as **spectral absorptivity**:

$$A_\theta\,(\mathbf{g}) = E_{\omega\in\Omega}\big(A_{\theta,\omega}(\mathbf{g}) \times I_{\mathrm{AM15}}(\omega)\big) \tag{3}$$

We focus on two types of efficiencies:

Average **half-day** absorptivity: from sunrise to noon where $\theta_{max} = \pi/2$ , and
Average **full-day** absorptivity: from sunrise to sunset where $\theta_{max} = \pi$.

The most accurate way of computing $A_{\theta,\omega}(\mathbf{g})$ is by means of repeated Monte Carlo ray tracing simulations. A large sample size of random rays colliding with the plane of solar cell is generated and traced by means of the Fresnel's Law of reflection/absorption, until the ray is either absorbed in the cell, or completely fades away. Absorptivity is the fraction of simulations in which light is absorbed. Since sunlight is un-polarized, at every wavelength $\omega$, both p-polarized and s-polarized radiations must be considered and simulated. When a ray reaches a surface at an angle $\theta_i$ (with respect to the surface normal), the ray is reflected with probability $R$ or absorbed with probability $1 - R$, where $R$ is the reflectance factor of silicon. $R$ is determined by Fresnel's equations and depends on the incident angle, polarization and refractive index of silicon, which in turn is a function of wavelength according to the following equations:

$$R_s = \left| \frac{\cos(\theta_i) - \mathbf{n}(\omega)\sqrt{1 - \left(\frac{\sin(\theta_i)}{\mathbf{n}(\omega)}\right)^2}}{\cos(\theta_i) + \mathbf{n}(\omega)\sqrt{1 - \left(\frac{\sin(\theta_i)}{\mathbf{n}(\omega)}\right)^2}} \right|^2 \quad (4)$$

for the s-polarized wave, and:

$$R_p = \left| \frac{\sqrt{1 - \left(\frac{\sin(\theta_i)}{\mathbf{n}(\omega)}\right)^2} - \mathbf{n}(\omega)\cos(\theta_i)}{\sqrt{1 - \left(\frac{\sin(\theta_i)}{\mathbf{n}(\omega)}\right)^2} + \mathbf{n}(\omega)\cos(\theta_i)} \right|^2 \quad (5)$$

for the p-polarized wave. $\mathbf{n}(\omega) = n_\omega + ik_\omega$ is the complex refractive index of silicon at wavelength $\omega$. $n_\omega$ and $k_\omega$ are depicted in Figure 2 along with AM1.5 solar irradiance.

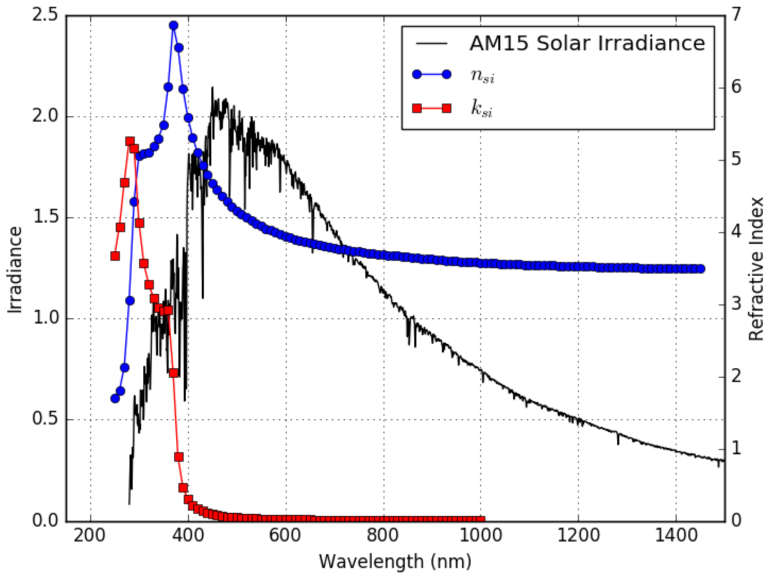


Fig. 2. Refractive index of silicon and AM1.5 solar irradiance.

Solar absorptivity $A_{\theta,\omega}(\mathbf{g})$ is a direct measure of the amount of power that the solar cell absorbs for a particular incident angle and wavelength. In order to have a normalized quantity, we define it as the relative amount of power that the solar cell absorbs compared to that of a fully absorbing solar tracking flat cell of the same length $L$. In other words, we measure energy per base area. Therefore, $A_{\theta,\omega}(\mathbf{g})$ is multiplied by a normalization factor $L'/L$ where $L'$ is the length of the cross section of the light ray that reaches the cell as shown in Figure 3.

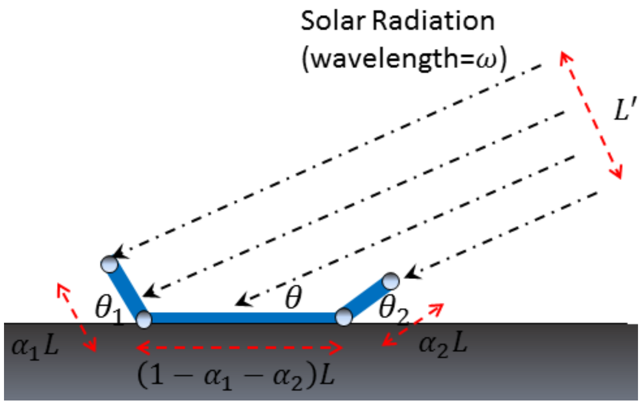


Fig. 3. Cross section demonstration of the 3 piece folded panel and incident ray of light.

## SURROGATE MODELING

The calculation of (3) is an intense numerical optimization that has to iterate a large number of ray tracing simulations over all incident angles and wavelengths, and therefore is largely time-consuming. To overcome the computational hassle, we propose using a surrogate model for learning the spectral absorptivity. First note that spectral absorptivity is a function of geometry parameters and solar angle $\theta$:

$$A_\theta(\mathbf{g}) = F(\alpha_1, \alpha_2, \theta_1, \theta_2, \theta) \tag{6}$$

We aim to estimate $F(\cdot)$ using a surrogate model that can be calculated directly without having to do intense MC calculations. For simplicity, we denote the vector of parameters with $\mathbf{x}$:

$$\mathbf{x} = (\alpha_1, \alpha_2, \theta_1, \theta_2, \theta) \tag{7}$$

If $\hat{F}(\cdot)$ is the approximate surrogate function for $F(\cdot)$, then the overall optical absorptivity can be approximated by:

$$\hat{A}(\mathbf{g}) = E_{0\leq\, \theta\leq\theta_{max}}\big(\hat{F}(\mathbf{x})\big) \tag{8}$$

The learning model that we propose to use is that of an artificial neural network. A neural network is a feed-forward structure that consists of an input layer, multiple hidden perceptron layers and an output layer with a single neuron that delivers the estimated value, as depicted in Figure 4. The output of every layer is sequentially passed to the next layer. Every neuron implements a basic function on a linear combination of the inputs. Since the output value is an absorption fraction and is known to be between 0 and 1, we use sigmoid activation functions for all the neurons in the network [13]. The parameters of the network are the weights of the neurons inside the network, which are the coefficients of the linear combination and constant biases. For more details on the structure of the neural network and definitions of perceptron, we refer the reader to [13]. We restrict our study to networks with the same number of perceptrons in every hidden layer.

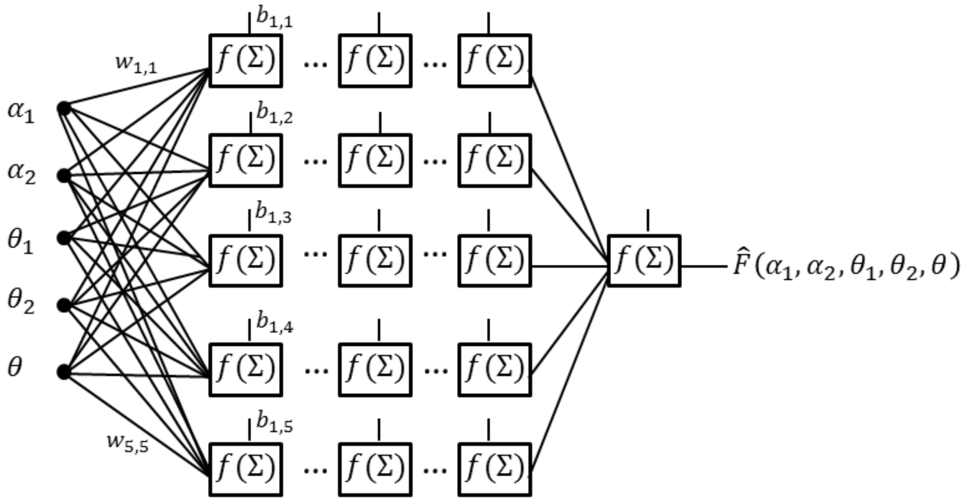


Fig. 4. Schematics of a generic neural network.

## NUMERICAL RESULTS

**Model Fitting.** In order to select the best fitting model and applying it to optimization, we generated two sets of 1000 random **x** vectors. Parameters of every vector are selected uniformly at random from the following ranges:

$$0 \leq \theta_1, \theta_2, \theta \leq \frac{\pi}{2}, 0 \leq \ \alpha_1, \alpha_2 \leq 0.4 \tag{9}$$

We consider a choice of a neural network with 1 to 3 hidden layer and 2 to 5 neurons per hidden layer. For every such model, we train the network on the first set of 1000 data points using the back propagation algorithm [13], and apply the model to the second 1000 data points as a measure of fitness. The model with the least square error on the second data set is selected as the model choice. The selected model in our study is a network with 3 hidden perceptron layers and 5 nodes per layer. A bin-plot of estimated absorptivity values versus true absorptivity values over the second dataset for the selected network is plotted in Figure 5, which demonstrates a high correlation.

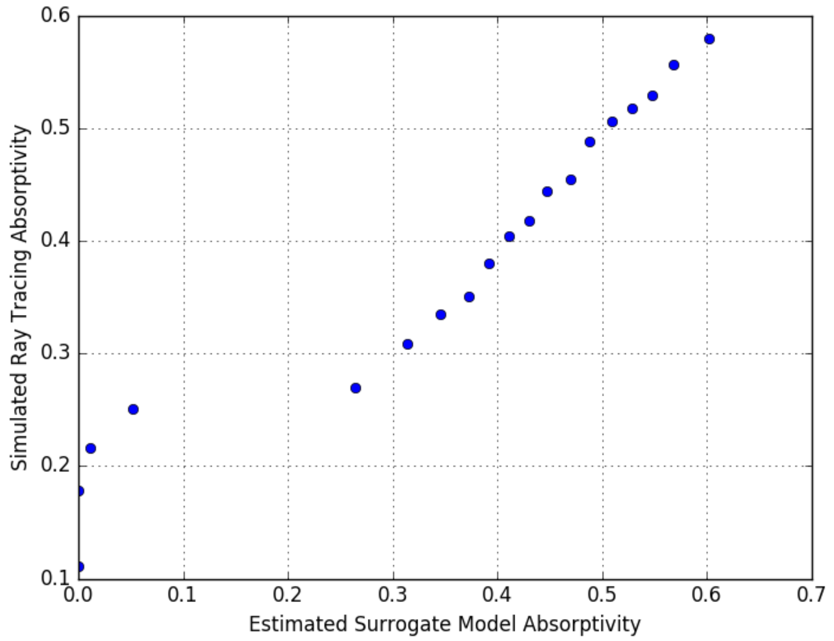


Fig. 5. Quantile bin-plot of estimated absorptivity for out-of-sample data using the surrogate model versus the accurate MC based calculation of absorptivity.

**Optimization Using the Surrogate Model.** Optimization of $A(\mathbf{g})$ is done using the surrogate model $\hat{A}(\mathbf{g})$ based on the best choice of neural network explained in the previous section. Mathematically, the optimization is formulated as:

$$\max_{\mathbf{g}} E_{0\leq\ \theta\leq\frac{\pi}{2}, \omega\in\Omega}\left(\hat{A}_{\theta,\omega}(\mathbf{g}) \times I_{\mathrm{AM15}}(\omega)\right) \tag{10}$$

which is a very fast procedure by means of exhaustive numerical search. The resulting parameters of optimization are listed in Table 1.

Table 1
Values of Optimal Parameters for Half-Day and Full-Day Optimization Using Surrogate Model

| Optimization type | Parameter name | | | |
|---|---|---|---|---|
| | $\alpha_1$ | $\alpha_1$ | $\theta_1$ | $\theta_2$ |
| Half day | 0.3 | 0.1 | $0.25\pi$ | 0 |
| Full day | 0.3 | 0.1 | $0.14\pi$ | $0.14\pi$ |

With these values for the vector **g**, we calculate the absorptivity at different incident angles from 0 to $\pi/2$ using accurate ray tracing. The results are compared with that of the surrogate model and the flat cell. Absorptivity values versus angle of incident for the optimized cells in the half-day and full-day optimizations are shown in Figures 6 and 7, respectively. Note that the surrogate model absorptivity values are very close to those calculated using accurate MC simulations.

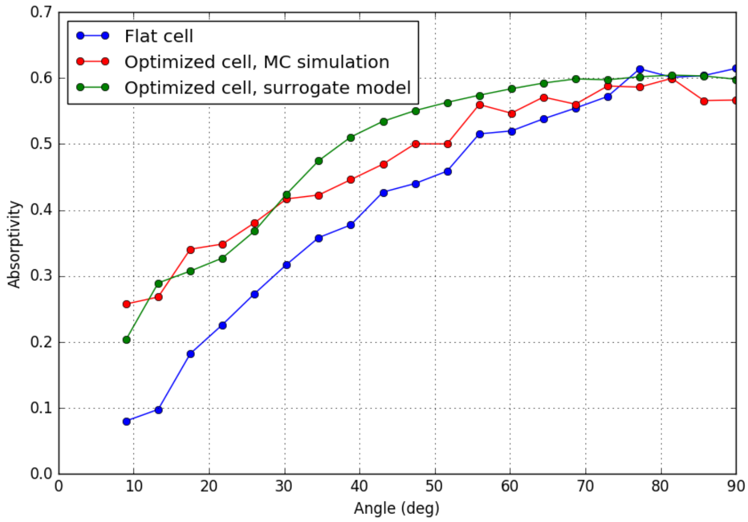


Fig. 6. Absorptivity versus incident angle for the 3 piece panel optimized using the surrogate model for half-day average radiation and the flat panel.

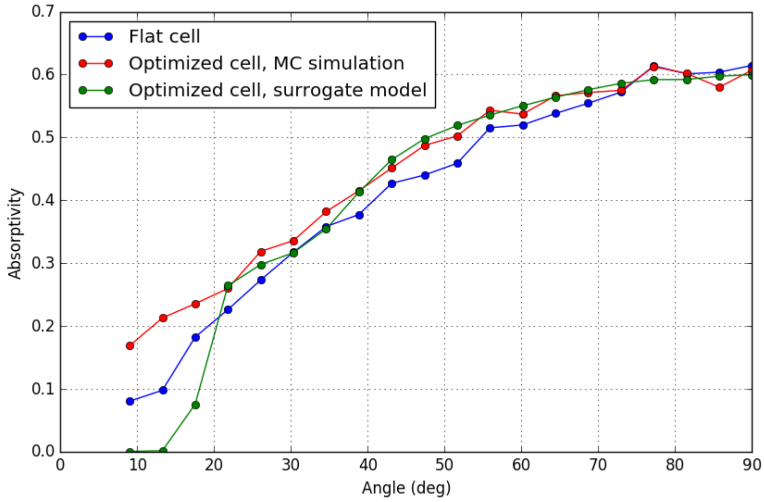


Fig. 7. Absorptivity versus incident angle for the 3 piece panel optimized using the surrogate model for full-day average radiation and the flat panel.

Average absorptivity factor for the flat cell is 0.419. For the model of half-day optimization, neural network surrogate model suggests absorptivity of 0.495, while the true ray tracing based absorptivity is 0.475. The optimal design has thus a 13% improvement over the flat cell. For optimal full-day optimization, the improvement is close to 7%. These values are listed in Table II below.

Table 2
Average Absorptivity Values for Flat and Optimized Cells

| Optimization type | Flat cell | Optimized cell MC | Optimized cell surrogate |
|---|---|---|---|
| Half day | 0.419 | 0.475 | 0.495 |
| Full day | 0.419 | 0.448 | 0.420 |

## CONCLUSION

In this paper, a novel solar cell structure is proposed that consists of three pieces of flat panels joint together with particular tilt angles. The optimal design of the geometry of the three-piece solar panel is then studied in order to maximize the optical efficiency of the cell.

The efficiency of the solar cell is measured with respect to the average radiation angle and the standard AM1.5 irradiance. Two average absorptivity objectives are considered in this work: the half-day absorptivity and the full-day absorptivity. Then, the Monte Carlo optical ray tracing method is applied to obtain the accurate efficiency values of the solar cell, which requires a large number of iterative computations. Thus, in order to resolve the low design efficiency with the optical ray tracing method, a surrogate model is established from 1000 random samples using artificial neutral networks, which calculates the absorptivity of the solar cell as a function of four geometry parameters and the radiation angle. The simulated results reveal that the model is able to estimate the absorptivity with high accuracy over the out-of-sample data. Furthermore, the surrogate model can be reliably used to optimize the geometry of the proposed structure without the need for intense first principle Monte Carlo simulations.

In future work, we aim to generalize the proposed design to multiple-fold pieces and curved solar structures, and develop advanced surrogate models that can estimate optical response of such structures very accurately. Curved structured are also used in join electrical-thermal solar applications. Developing surrogate models for numerically modeling those designs and consequently optimizing energy conversion utility functions based on approximate models is another highly interesting extension of the ideas and methodologies of the current work.

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