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ELECTRICAL CHARACTERISTIC OPTIMIZATION OF SILICON SOLAR CELLS USING GENETIC ALGORITHM

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Abstract

Thin-film solar cell is one of cost-effective energy technologies potentially. Optimal design of thin-film solar cell for pursuing the highest efficiency is achieved in a trial-and-error engineering way. In this work, a device simulation-based genetic algorithm (GA) is applied to optimize the dark and illuminated properties of a-Si thin-film solar cells. A set of solar cell transport equations consisting of the Poisson equation, electron-hole current continuity equations, and the photogeneration model is solved numerically. The results of device simulation are used for the optimization of the electrical characteristics via the GA method; therefore, we can deduce optimal seven parameters including the five structural parameters and two doping concentrations of explored solar cell. The iteration of evolutionary is terminated when the final convergent solution is obtained. The evolutionary technique enables us to optimize the associated electrical characteristics, such as the short-circuited current, the open-circuited voltage, and the maximum efficiency of the examined *p-i-n* solar cell.

Key words: silicon thin-film solar cell, transport model, numerical simulation, genetic algorithm, simulation-based, evolutionary methodology, efficiency, p-i-n structure

1. INTRODUCTION

Solar cell (Nelson, 2003) provides renewable and clean energy by converting sunlight to electrical power, which has attracted much attention in the decades. Despite the growing importance, we need to reduce the fabrication cost of solar cells and increase the energy conversion efficiency (η) before they can successfully replace fossil fuel for electrical power generation. At present, the materials of crystalline silicon (c-Si), polycrystalline silicon (poly-Si), amorphous silicon (a-Si), wafer and bulk materials are the main developed silicon-based materials using in producing solar cells (Luque et al., 2002). Optimal design of thin-film solar cell for pursuing the highest efficiency could be achieved in a trial-and-error way iteratively. On the other hand, genetic algorithm (GA) is a population-based global search optimization method based on the mechanics of natural selection, and often considered as the most famous branch in evolutionary algorithms. The GA with the appropriate elitist policy can guarantee the global best solution acquirement theoretically and generally can provide many near-optimal selections of the problem. Real-world problem solving using GA has shown promising observation. For example, it has been modified in various types and used in engineering domains. For example, inverse doping profile problem (Li et al., 2007), optimal circuit design (Li, 2009; Tao et al., 2008; Lo, 2010), antenna electromagnetics (Li, 2010). These applications of GAs have demonstrated many interesting designs in optimization of electrical engineering problems. For a basic *p-i-n* structure of a-Si thin-film solar cell, the efficiency is 5% (Nelson, 2003). Therefore, characteristic optimization of a-Si solar

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cell, using a device simulation-based GA methodology, is an interesting approach for solar cell technologies.

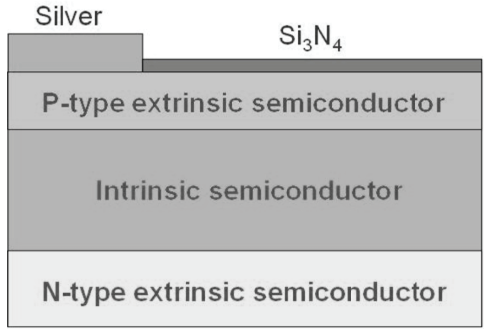
In this work, based upon a unified optimization framework (UOF), a device simulation-based GA is implemented for a-Si thin-film solar cell optimization problem. To calculate the device characteristic, a set of solar cell transport equations consisting of the Poisson equation, electron-hole current continuity equations, and the photo-generation model is solved numerically. The results of device simulation are used for the fitness calculation and then the evaluation of designing parameters' quality via the GA. Notably, there are seven parameters including the five structural parameters and two doping concentrations of explored solar cell. The iteration of evolutionary process is terminated when the results meet the prescribed targets. The results of our optimization have allowed us to calculate the associated electrical characteristics, including short-circuited current (I_{sc}), open-circuited voltage (V_{oc}), and maximum efficiency to analyze the properties of the solar cell. This approach has practical applications in solar cell characterization and structure optimal design.

This paper is organized as follows. In the section II, we give a brief description of the examined a-Si thin-film solar cell and parameters to be optimized. In the section III, we introduce the simulation-based optimization technique. Then, we show the optimization results and discussion in the section IV. Finally, we draw the conclusion and suggest future work.

2. THE EVOLUTIONARY METHODOLOGY

2.1. The a-Si Thin-Film Solar Cell and Transport Equations

For real world application of solar energy, it is important to decrease the manufacturing cost process and increase the efficiency of power conversion. Providing minority carrier diffusion lengths exceed typical absorption depths, *p-n* junctions make efficient photo converters with high collection efficiency. However, c-Si is expensive to produce and so there is a great deal of interest in finding photovoltaic materials of less demanding material quality which can be grown more cheaply. At present, a-Si has been identified as one of the best materials with the advantage mentioned above. This thin film material is usually produced by physical or chemical deposition techniques which can be applied to large areas and throughputs.



Parameters to be optimized of the studied *p-i-n* solar cell

- Thickness of silver: **FrontContactThickness,** cm^{-3}
- Thickness of the anti-reflection layer: **FrontArcThickness,** μm
- Thickness of the all semiconductors: **SubstrateThickness,** μm
- Doping concentration of the *p*-layer: **FrontDopingConcentration,** cm^{-3}
- Dopant depth of the n-layer: **FrontDopingDepth,** μm
- Doping concentration of the *n*-layer: **BackDopingConcentration,** cm^{-3}
- Dopant depth of the n-layer: **BackDopingDepth** (μm)

Fig. 1. *Plot of the optimized a-Si solar cell with the p-i-n structure. The parameters to be optimized include the layer's thickness and doping profile of each layer.*

The basic structure of a-Si solar cell is a *p-i-n* structure, as shown in the figure 1. The silver and Si_3N_4 are the front contact metal and anti-reflection layer. Since diffusion lengths are so short in doped a-Si, the central undoped or intrinsic region is needed to extend the thickness over which photons may be effectively absorbed. In order to exploring the physical operation in solar cells, the three governing equations which include Poisson equation and continuity equations for charge transportation in semiconductor are induced and shown in follows (Li, et al., 2002).

$$\nabla^2 \phi = -\frac{q}{\varepsilon_s}\left(p - n + N_D - N_A\right) - \rho_{trap} \quad (1)$$

$$\frac{\partial n}{\partial t} = \frac{1}{q}\nabla \cdot J_n + G_n - U_n \quad (2)$$

and

$$\frac{\partial p}{\partial t} = -\frac{1}{q}\nabla \cdot J_P + G_P - U_P\,, \quad (3)$$

where the ε is the electrical permittivity, q is the elementary electronic charge, n and p are the electron and hole densities, N_D is the concentration of ionized donors, N_A is the concentration of ionized acceptors, ρ_{trap} is the charge density contributed by traps and fixed charges, $G_{n/p}$ is the rate of generation of electrons, U_n and U_p are the rates of recombination, J_n is the electron current density, and J_p is the hole current density. The Eqs. (1)-(3) indicate that the number of carriers is conserved and the electrostatic potential due to the carrier charges obeys Poisson's equation. Generation is an electronic excitation event which increases the number of free carriers available to carry charge; recombination is an electronic relaxation event which reduces the number of free carriers. For the studied a-Si thin-film solar cells, the most important form of generation G_n and G_p is optical generation G^{opt} (Sze, 1981).

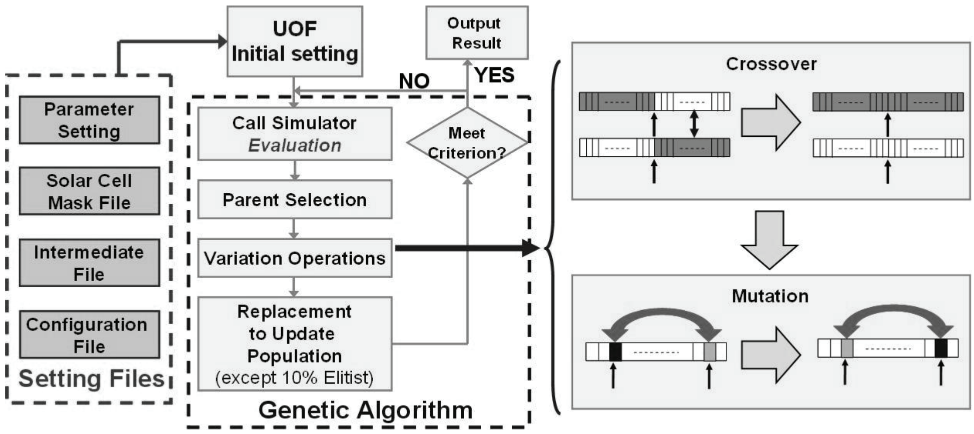


Fig. 2. The proposed optimization technique based upon UOF (Li et at., 2008) to improve the electrical characteristics and efficiency of the tested a-Si solar cell.

3. THE SIMULATION-BASED GENETIC ALGORITHM

The adopted technique integrates genetic algorithm and numerical semiconductor device simulator on the unified optimization framework (UOF) (Li et at., 2008) is used to optimize the performance of a-Si thin film solar cells. The UOF provides basic interfaces to define a general problem and generic solver, enabling these two different research fields to be bridged. The components of the UOF can be separated into problem and solver components. These two parts work independently allowing high-level code to be reused, and rapidly adapted to new problems and solvers. The main reason of the integration is for the fitness value requirement of an individual (in this study, it means certain parameter configuration of a-Si solar cell, which is formulated as a real number array. An element in the array is usually called a gene in GAs) in the GA. UOF supplies it via the desired characteristic of the individual by executing external simulator. Generally speaking, the process to calculate fitness value of an individual is called "evaluation" in GAs. The value represents how "good" the individual is in the optimization problem. In this study, the maximum efficiency, V_{oc}, and I_{sc} are set as fitness values and the technique applies these setting to optimize the parameter configuration, respectively.

The whole optimization flow of the technique is shown in figure 2. In the mask file and parameter setting file, we define the given structure and the parameters to be optimized of the a-Si solar cell. Then the population, which means the group of parameter configurations, is initially generated randomly or by engineering experiences. After the initial population established, all individuals in the population are evaluated. Then the GA accords fitness value proportional (ranking) selection to pick the parents (the better individuals under probability). Crossover is used as the first operator applied on the parents. The genes (parameters in the array) of an offspring from beginning to split point (randomly determined afresh in each offspring production) will be inherited by one parent, and the rest will be inherited by the other. The second operator, mutation, enables to randomly choose two genes in one individual and exchange them under the probability of mutation rate. Finally, except the best 10% individuals in old

Table 1. The optimized a-Si solar cell structures and performances – Efficiency case.

Parameters		Range	Efficiency optimized case
Substrate Thickness, μm		0.5~1	0.65
Front Contact Thickness, cm^{-3}		0.05~0.3	0.3
Front Arc Thickness, μm		0.02~0.2	0.04
Back Doping Concentration, cm^{-3}		1e18~1e20	6.8e19
Back Doping Depth, μm		0.01~0.2	0.2
Front Doping Concentration, cm^{-3}		1e18~1e20	4.8e19
Front Doping Depth, μm		0.001~0.1	0.092
Performance	Effeciency η (%)		8
	V_{oc} (voltage)		1.1693
	I_{sc} (mA/cm^2)		7.7

population, which are called elitists, the other part of the old population is substituted by the offspring after variation operators. Iteratively, a new population established and next generation of evolution starts from evaluation step until the stop criterion are met.

4. RESULTS AND DISCUSSION

The results, as listed in the tables 1 and 2, include the optimized a-Si solar cell structures and performances to the maximum efficiency, V_{oc}, and I_{sc}, respectively. In the result tables, the '**FrontContactThickness**' is the thickness of silver, the '**FrontArcThickness**' is the thickness of the anti-reflection layer, the '**SubstrateThickness**' is the thickness of the all semiconductors (*p*-layer, *i*-layer and *n*-layer), the '**BackDopingConcentration**' and '**BackDopingDepth**' are the doping concentration of the *N*-type semiconductor (*n*-layer) and its thickness, and the '**FrontDopingConcentration**' and '**FrontDopingDepth**' are the doping concentration of the *P*-type semiconductor (*P*-layer) and its thickness, in which the unit of thickness is um and the doping concentration is cm^{-3}.

Table 2. *The optimized a-Si solar cell structures and performances – V_{oc} and I_{sc} cases.*

Parameters		Range	V_{oc} optimized case	I_{sc} optimized case
BackDopingConcentration, cm^{-3}		5e18~1.5e19	1.5e19	7e18
BackDopingDepth, μm		0.01~0.05	0.05	0.03
FrontDopingConcentration, cm^{-3}		4e19~8e19	8e19	8e19
FrontDopingDepth, μm		0.005~0.015	0.015	0.005
Performance	Effeciency (η)		5.34	5.65
	V_{oc} (voltage)		1.0124	1.0038
	I_{sc}, mA		6.34	6.75

To estimate the electrical characteristics of solar cell we use the simulated reflectance spectra. Property of optical system directly affects the short-circuit current density and the conversion efficiency of a solar cell; therefore, the open-circuit voltage, and the solar cell conversion efficiency The short-circuit current density and open-circuit voltage of the solar cell are calculated under the standard AM1.5 global spectrum from its current and voltage (I-V) characteristics. Then, solar cell's efficiency (η) deduced from V_{oc}, I_{sc}, is given by:

$$\eta = \frac{P_{\max}}{I_{sc}V_{OC}}\frac{I_{SC}V_{OC}}{P_I} = \frac{P_{\max}}{P_I} \times 100\%, \qquad (4)$$

where, P_I designates the incident power (P_I = 0.1 W/cm^2 under illumination AM 1.5 G) and the P_{max} is the largest electrical power the solar cell can deliver. First, we give a proper range of the parameters of the structure to optimize the efficiency. As shown in table 1, the efficiency of optimization result is 8% which is about 2.32 percent improvement of default case for our structure efficiency, 5.68%. In addition, we can see that the '**FrontDopingDepth**' is the largest value and the '**BackDopingDepth**' is the smallest value of our parameter ranges, which shows the fact that higher '**FrontDopingDepth**' and lower '**BackDopingDepth**' are the superior design strategy for thin film a-Si solar cells. Furthermore, we discover that the thickness of anti-reflection layer for decreasing the sunlight reflectance might be lower than 50 nm in our case. Second, we apply different parameter range but same structure (here we don't consider the '**SubstrateThickness**', '**FrontArcThickness**' and '**FrontContactThickness**') to maximize the V_{oc} and I_{sc} respectively. The results show that the '**FrontDopingConcentration**' should be high for both improving V_{oc} and I_{sc}. However, the maximizations of these two parameters would sacrifice the efficiency which are 0.34 and 0.03 lower than the default value. It implies the trade-off relationship between V_{oc} (I_{sc}) and η.

By considering the process in the experiment of optimization, figure 3 shows the normalized fitness value convergence behaviors of three objectives versus number of generation in the GAs. Here the fitness values indicate efficiency, V_{oc}, and I_{sc} thus we want to maximize them. It illustrates that all three best values are achieved after 20th generation. So we set "after 30th generation over" as the stop criterion in a run (execute the optimization technique a time) of optimization is reasonable and can save the consumption of time. Several runs are done and the best is chosen as the final result. A run spends about six hours in the condition that population size is 50.

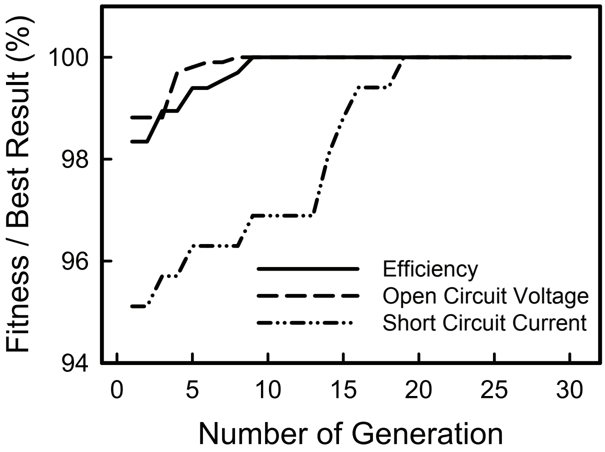


Fig. 3. *The normalized fitness value (Efficiency, V_{oc}, I_{sc}) versus the number of generations. The fitness is normalized with respect to the best result of each run.*

5. CONCLUSIONS

In this study, an optimization method integrates genetic algorithm and numerical semiconductor simulator is tried to solve the a-Si solar cell design optimization problems and achieves satisfying results. The structure parameters are optimized, and the objectives are important performance metrics of solar cells like efficiency, V_{oc}, I_{sc}. For the results, these metrics have the best values about 8% (Efficiency), 1.1693 V (open circuit voltage), and 7.7 mA (short circuit voltage). They are consistent with the theoretic physical limitations of the a-Si solar cell. The excellent performances of the optimization technique not only provide some superior structure configurations but also imply that the approach has enough capability to solve other solar cell design problems with complicated structure – more optimized variables. Currently, we apply this method to optimal design of HIT solar cells. Furthermore, for the aim of spending less time, distributed computing technique will be considered.

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OPTYMALIZACJA CHARAKTERYSTYK ELEKTRYCZNYCH KRZEMOWYCH BATERII SŁONECZNYCH PRZY UŻYCIU ALGORYTMÓW GENETYCZNYCH

Streszczenie

Cienka bateria słoneczna jest jedną z najbardziej oszczędnych technologii energetycznych. Zaprojektowanie optymalnej z punktu widzenia efektywności baterii słonecznej jest zwykle robione metodą prób i błędów. W niniejszej pracy do optymalizacji własności krzemowej cienkiej baterii słonecznej zastosowano algorytmy genetyczne. Układ równań transportu dla baterii słonecznej, składający się z równania Poissona, równania ciągłości dla dziury elektronowej oraz modelu fotogeneracji, jest rozwiązywany metodami numerycznymi. Wyniki symulacji wykorzystano do optymalizacji charakterystyk elektrycznych baterii stosując algorytm genetyczny. W konsekwencji wyodrębniono siedem optymalnych parametrów strukturalnych i dwa parametry koncentracji donorów w analizowanej baterii. Ewolucyjna procedura iteracyjna jest zatrzymywana po uzyskaniu zbieżności rozwiązania. Technika ewolucyjna umożliwia optymalizację takich charakterystyk elektrycznych jak prąd zwarcia, napięcie otwartego obwodu elektrycznego oraz maksymalna wydajność baterii słonecznej *p-i-n*.

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