Research on Modeling and Power Algorithm of Photovoltaic Cells for Solar Cars

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Abstract. Solar photovoltaic cells will be an effective supplement to electric vehicle batteries. In order to make the photovoltaic system of the solar car provide reliable power, this paper models the photovoltaic cell and designs the maximum power point (MPP) tracking algorithm based on three-point sampling with a fixed voltage. In addition, considering that the output power will change when the voltage and radiation intensity change under the peak power of the solar vehicle, the prediction of the peak output power of the photovoltaic array considering the influence of the radiation intensity and battery voltage is put forward for the first time. Experiments show that the designed power algorithm runs stably, and the power generation power prediction error is less than 1%. The peak output power prediction of the photovoltaic array takes into account the effects of real-time radiation intensity and battery voltage fluctuations, making the peak power prediction of the vehicle more accurate.

Keywords: Solar car, photovoltaic cells, modeling, maximum power generation, peak power prediction.

1. Introduction

Solar cars add solar energy as an energy source on the basis of electric cars, which can give full play to the environmental advantages of solar energy. At present, if the solar energy acquisition and utilization need to be accurately described in a mobile solar car, it can only be solved by component testing[1]. Because of cost considerations, solar cars do not have strong computing power. Therefore, based on the hardware components of solar cars, it is very important to establish a reliable photovoltaic cell model, and design an efficient and stable MPP tracking algorithm and peak output power prediction algorithm[2]. Based on the I-V characteristic curve of photovoltaic cells, many models have been established such as single diode model[3], double diode model[4] and modified double diode model. However, due to the large number of parameters of the dual-diode model and nonlinear coupling, the calculation of this type of model is complicated[5]. The model of a single diode is simple, and the amount of calculation is small, so the single-diode model is more widely used. Ali A N et al [6] and Pandey S V et al [7] both set up a photovoltaic simulator in consideration of irradiance and temperature, and explore the SOC and voltage changes of the battery under the state of charge. Singh B et al [8] uses the Lagrangian relaxation algorithm to optimize the hybrid solar cell system. Raj P J et al [9] explores the charging status of photovoltaic cells at the maximum power point based on fuzzy logic. The environment variables set by these schemes are relatively single, which does not correspond to the actual changed environment. Chitita S et al [10] considers the dynamic changes of weather conditions and load demand, and uses dual PI compensators to balance the power of the photovoltaic array and the battery. Baili Z et al [11] builds a photovoltaic power plant power prediction model based on genetic algorithm and BP neural network algorithm, and optimizes the
initial weight and threshold of the neural network. These two schemes can predict photovoltaic power generation well, but require complex and powerful embedded systems and a lot of preliminary research. It does not meet the characteristics of solar cars that focus on practicability and low cost. So the purpose of the paper is to establish a photovoltaic cell model of solar vehicles, study its maximum power generation algorithm and peak power prediction algorithm, accurately estimate the power state of solar cars, and improve the performance of solar cars.

2. Modeling and Simulation

2.1. Photovoltaic Cell Type and Arrangement

The solar system of a solar car can independently drive the motor, the power of its solar power generation will also be the content that needs to be considered in battery management. As a mobile solar system, its power generation efficiency will be affected by changes in the external environment and restrictions on the shape of the body structure, so model selection and group arrays are particularly important. Therefore, SunPower’s Me3 monocrystalline silicon solar panels are used for grouping, which has high conversion efficiency, small size, and is convenient for array design. With flexible processing technology, the solar panel array can be better attached to the roof of the car. Some parameters of Me3 are shown in Table 1.

| Parameters                  | Values          | Parameters                  | Values          |
|-----------------------------|-----------------|-----------------------------|-----------------|
| Packing factor              | 82.9%           | Open-circuit voltage        | 0.727V          |
| Efficiency                  | 25%             | Maximum power               | 3.89W           |
| Size                        | 125mm*125mm     | Voltage at the MPP          | 0.64V           |
| Short-circuit current       | 6.45A           | Current at the MPP          | 6.08A           |

Table 1. Parameters of single Si photovoltaic cell Me3.

In order to prevent the damage of local photovoltaic cells from affecting the overall solar system, the solar panels of the solar car are divided into multiple arrays. To study the power characteristics of photovoltaic cell systems, Maximum power point tracker (MPPT) is required to regulate the maximum power generation, and to predict the output power of the solar panel under the dynamic voltage output by the battery peak power duration. Therefore, this paper selects a set of 32 solar panels as the object to study the MPPT control algorithm and power prediction based on the influence of the external environment.

2.2. Modeling and Characteristic Simulation

The single diode model is used to model the Me3 solar cell, and according to the Kirchhoff’s theorem, the output current of solar panels is expressed as below.

\[ I = I_{ph} - I_{fD} - I_{sh} \]  \hspace{1cm} \text{(1)}

\[ s.t. \quad I_{fD} = I_0 \left[ \exp \left( \frac{q(U + IR_s)}{AKT} \right) - 1 \right] \]  \hspace{1cm} \text{(2)}

\[ I_{sh} = \frac{U + IR_s}{R_{sh}} \]  \hspace{1cm} \text{(3)}

where \( I_0 \) denotes the reverse saturation current of a solar cell under the condition of zero radiation; \( q=1.6\times10^{-19}\text{C} \) denotes the unit charge; \( A=1.2 \) is the correction factor; \( k=1.38\times10^{-23}\text{J/K} \) is the Boltzmann constant; \( T \) denotes the surface temperature of the cell.

In the real-world solar-assisted EV, if a solar panel array is composed of \( N_s \) solar panels in series and \( N_p \) panels in parallel, the actual equivalent current is calculated as

\[ I = I_{ph} - I_d - I_p \]  \hspace{1cm} \text{(4)}
Series current \[ I_p = \frac{UN_p / N_i + IR_i}{R_{sh}} \]  

Parallel current \[ I_d = \left( \exp \left[ \frac{q(U / N_i + IR_i / N_p) - 1}{AKT} \right] \right) I_o N_p \]  

Establish a photovoltaic cell array model, and set up a 32-cell module array according to the single-cell parameters in Table 1. The open-circuit voltage is set to 23.264V, the short-circuit current is 6.45A, and the series-parallel connection is 32S1P. Solar panels are greatly affected by temperature and radiation intensity, so setting different solar radiation intensity and temperature. And get the characteristic curve of the solar panel array as shown in Figure 1.

From Figure 1(a), with the increase of radiation intensity, the short-circuit current and maximum power of the solar panel array increase rapidly. In addition, as the radiation intensity increases, the voltage at the MPP increases slightly. Based on the simulation, the power generation of solar panels is greatly affected by the radiation intensity, but less affected by the temperature (only the temperature difference is larger than 10°C, the power generation is affected, which is not apparent in the practical application). Therefore, the short-term power generation prediction of solar vehicles can neglect the temperature, and only consider the influence of radiation intensity on the MPPT algorithm.

3. Power Algorithm Design

3.1. MPPT Tracking and Power Prediction

In this study, we adopt the adaptive fixed voltage numerical optimisation to track the MPP. The flowchart of this algorithm is depicted in Figure 2. The primary principle is to preliminarily determine the MPP, and then sample the power conditions at three points. Through simulating the characteristic curves, the MPP position can be solved. The above MPP can be modified by comparing the real-time power and the estimated power through the hysteresis comparison method. Finally, the real-time MPP of the solar panel array can be obtained cyclically. The details are expressed as follows.

1. Before connecting the loads to the solar panels, open circuit voltage is measured, and the preliminary estimation of the MPP is calculated with \( V_{set1} = k \times V_{oc} \). The MPPT devices regulate the power switches to set the output voltage \( V_{set1} \) and then sample the output current. Accordingly, the output power of the first point can be calculated. (2) The second and third points are determined by adding the disturbance variables. Specifically, two disturbance variables \( -\Delta V \) and \( \Delta V \) on the left and right sides of \( V_{set1} \) are determined, and then the MPPT devices would track these two voltages and calculate their output powers as the second and third points. (3) Use Newton interpolation method to find the MPP. (4) The MPPT device regulates the operative voltage to the calculated maximum voltage point, i.e. \( V_{set} = V_{max} \), and the maximum power \( P_{max} \) can be determined.
3.2. Correction of the SOP Based on the Real-time Generated Power

In the actual environment, the conversion efficiency of MPPT will be affected by the load and battery voltage, which would impact the accurate prediction of SOP state of batteries. To accurately predict the effective output power of MPPT, the following modification is adopted in this study. Since the duration of the peak power is relatively short, the temperature change can be regarded as a constant in the control period and only the radiation intensity is considered. The final predictive power selects the minimum predictive power within a continuous duration. Therefore, the power prediction correction for L sampling periods at current time \( k \) can be processed by the following formula.

\[
P^{\text{max,k+L}}_{\text{out}} = \min \left( \sum_{i=1}^{L} I^{i}_{k,k+1} \eta S \right)
\]

where \( I^{i}_{k,k+1} \) denotes the radiation intensity at timeslot \( i \), and \( \eta \) denotes the generated efficiency of the solar panels, and \( S \) is the effective area of the solar panel.

Another important factor is the dramatical voltage drop. When the battery voltage is pulled down to the cut-off voltage, the generated voltage of solar panel would also be pulled down, and the boosting efficiency would be affected meanwhile. Therefore, the predictive power of solar panels under the condition of the cut-off voltage of batteries can be formulated as follows.

\[
P^{\text{max,k+L}}_{\text{out}} = \min \left( P^{i}_{\text{max,k+1}} - P_{t} \lambda_{1} \right) \lambda_{2}
\]

where \( P^{i}_{\text{max,k+1}} \) denotes the peak generated power of solar panels during the timeslots \( \Delta t = L \times T_{s} \) and \( P_{t} \) is the current generated power. \( \lambda_{1} \) represents the factor on the generated power of solar panels when the battery voltage drops to the cut-off voltage. \( \lambda_{2} \) represents the booster efficiency of MPPT.

4. Results and Discussions

In this section, experiments are carried out to verify the designed power algorithm. Design a 4P7S battery pack in parallel with the photovoltaic cell array, and the signal acquisition system collects the experimental results. The power loads, solar-generated power, and battery power are presented in Figure 3. As shown in Figure 3(a), the experiment uses a variable load. The cycle of a set of loads is 400s. This experiment has gone through 17 cycles. From the view of Figure 3(b), the power of panels...
is stable almost without the heavy fluctuations when the SOC is larger than the allowance value 0.1, which manifests that the generated power of panels is not affected by the variant loads. After then, the generated power shows a larger fluctuation, which is caused by the variant battery voltage with lower SOC value less than 0.1. Overall speaking, the average generated power of the array is 91.2 W and the average efficiency of MPPT device is up to 96.29%. To validate the effectiveness of the proposed predictive generated power algorithm, we make a comparison with the actual measured generated power and the results are presented in Figure 4. It can be seen that the predictive generated power (according to equations 3 and 4) can well follows the change of the actual generated power and the predictive error is lower than 2W, which is profited from that the proposed predictive algorithm is not significantly affected by the variant battery voltage.

![Figure 3. The experimental results of solar panel power: (a) Measured load; (b) solar-generated power; (c) battery power.](image)

![Figure 4. Comparison of the solar generated power and predictive power: (a)Power;(b)Error.](image)

![Figure 5. The predictive results of the battery power and the total BMS. The change of SOC value and the resulting SOP value are illustrated in Figure 5. SOC estimation adopts extended Kalman filter algorithm. From the Figure 5(a), the initial SOC is sampled as 0.222,](image)
and after 17 operating cycles, the final SOC is lower than 0.017, which indicates that the battery pack is approaching to the full discharge. The peak generated power of the photovoltaic array shown in Figure 5(b) is lower than the predictive generated power in Figure 5(a) due to the impact of the peak voltage drop. Battery SOP prediction uses RC model algorithm based on SOC constraint. The predictive peak charging power of the battery pack is presented in Figure 5(c) and 5(d). Considering that excessive peak currents in the lower battery state would impair the battery pack, when the battery SOC decreases less than 0.1, the peak operating power would be constrained as zero in the SOP predictive algorithm. When the battery SOC value locates between 0.222 and 0.1, the predictive power in the SOP algorithm presents a decreasing tendency, which results in the increase of peak power of battery pack and the solar panels as shown in Figure 5(e) and 5(f). After comprehensively considering the maximal power, the increasing peak power of battery pack would promote the discharging limit, extending the travelling distance of the traditional electric vehicles.

5. Conclusion
This paper carries on the modeling and the power algorithm research to the photovoltaic cell of the solar car. Power algorithm includes MPPT maximum power tracking algorithm and real-time maximum output power prediction. Experimental results show that the solar energy utilization efficiency of the photovoltaic array reaches 23.4%, the conversion efficiency of the designed MPPT is higher than 96%, and the predicted power generation error is less than 1%. The peak output power prediction of the photovoltaic array takes into account the effects of real-time radiation intensity and battery voltage fluctuations, making the prediction data more accurate. At the same time, after adding the maximum power prediction of the photovoltaic array, the total peak charge and discharge capacity of the solar car battery system is improved. Designed models and algorithms provide a favorable basis for formulating more accurate energy management strategies.

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